Betting Markets as a Laboratory for Financial Studies

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Contents

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Zurich, November 2013 Raphael Flepp

Framework Paper

The *raison d'être* of financial markets is the allocation of capital. An optimal allocation of capital requires the financial markets to be informationally efficient, so that security prices fully reflect all available information (Fama, 1991). However, financial markets vary in their degree of market efficiency, or as Warren Buffett famously quipped: 'I'd be a bum on the street with a tin cup if the markets were always efficient'. Hence, the role of moderating factors that might affect the degree of market efficiency and the functioning of markets is a matter of an ongoing academic discussion. Central open questions include the following: Which market structure, a setting with an intermediary (a quote-driven market) or a pure exchange-based design (an order-driven market), exhibits higher market efficiency? Why do we observe a coexistence of quote-driven and order-driven market structures? To what extent does investor sentiment affect market efficiency? How does liquidity affect market efficiency?

Empirical studies of financial markets face a number of difficulties that prevent researchers from properly isolating the determinants of market efficiency. For instance, the fundamental values of traditional financial products are never revealed, because they are infinitely-lived. Therefore, all field studies must test market efficiency jointly with an equilibrium model that defines normal security returns (Fama, 1970). Moreover, comparisons of market efficiency and functioning across financial market structures are often hampered by differences in the assets traded and/or differences in macroeconomic conditions.

Betting markets exhibit a variety of unique properties that circumvent the problems that inhibit the investigation of conventional financial markets. Similar to securities and derivatives traded in financial markets, a bet is a state-contingent contractual claim on some future cash flow. Thereby, the cash flow is determined by the outcome of the bet's underlying event, e.g., a soccer match, and by the price of the contract, i.e., the odds on a specific event (Sauer, 1998). One major advantage of betting markets is that each betting contract possesses a prespecified end point at which the outcome (e.g., the winning of a particular team) becomes observable. The bet's odds may well deviate from its hypothetical fundamental value for some period of time, but at the end of the underlying event, the fundamental value of each betting contract is revealed. The observed outcome of a bet thereby serves as an indisputable benchmark against which the informational efficiency of market odds can be tested (Vaughan Williams, 1999). Additionally, a bet's underlying event is neither influenced by expectations of market participants or trading activity, nor is it influenced by macroeconomic factors.

Another feature that makes betting markets an interesting research field for financial studies is the coexistence of the quote-driven and the order-driven market structure, in which identical betting contracts are traded simultaneously (Verbeek, 2011). Similar to market makers in financial markets, bookmakers operate in a quote-driven market structure, serving as intermediaries between bettors. Thereby, bookmakers quote the odds at which they are willing to accept bets and participate in every transaction (Harris, 2003). Since 2000, betting exchanges have evolved in the betting industry. As order-driven financial markets, betting exchanges allow buyers and sellers to trade with each other in a continuous double auction, without the intermediation of bookmakers. In this market structure, two basic types of orders exist: limit orders and market orders. A market order is immediately executed at the best odds available, whereas limit orders have guaranteed odds, but the execution takes place only if there is a corresponding order on the opposite side of the market. If the limit order is not matched, it is placed in the limit order book until it is either executed or canceled (De Jong & Rindi, 2009).

Overall, betting markets offer a simple and clean research laboratory for financial market microstructure investigations. One goal of this dissertation is to compare the two different market structures in terms of market efficiency and price competitiveness. Moreover, this dissertation aims to explore how investor sentiment and liquidity influence market efficiency. These issues are individually addressed in four empirical papers.

The first paper, *The Impact of Market Structures on Market Efficiency: Evidence from the Betting Industry* (see Appendix A.1), investigates the comparative market efficiency of the quote-driven and the order-driven market structure. The impact of the market structure on market efficiency is an ongoing debate in the market microstructure literature and earlier studies have produced weak and/or inconsistent results (Madhavan, 1992; Biais, 1993; Masulis & Shivakumar, 2002; Theissen, 2000; Bennett & Wei, 2006).

We utilize the betting industry to compare the market structures in terms of market efficiency. Previous studies in betting markets have shown that the betting exchange market exhibits a higher market efficiency than the bookmaker market (Smith, Paton, & Vaughan Williams, 2006, 2009; Franck, Verbeek, & Nüesch, 2010). The paper expands this literature by employing a more comprehensive data set and a new econometric approach to address the comparative market efficiency.

Our data set consists of pairs of odds from the bookmaker and the betting exchange market from 9,562 matches played in the top five European soccer leagues. The results demonstrate that the odds from the betting exchange *Betfair* contain relevant information that is not fully included in the odds quoted by bookmakers. However, the odds from the bookmakers provide no additional information to the odds from the betting exchange. Thus, the quote-driven market exhibits lower market efficiency than the order-driven market. Taking advantage of the inefficient odds available at the quote-driven market leads to above-average, and in some cases even positive bettor returns.

To improve the design of markets, it is important to understand the impact of market structures on market efficiency. Thereby, the order-driven market structure seems to provide a more efficient algorithm for collecting and aggregating diverse information than profit-maximizing market makers.

The second paper, *The Liquidity Advantage of Quote-driven Markets: Evidence from the Betting Industry* (see Appendix A.2), examines the puzzling coexistence of the quote-driven bookmaker market and the order-driven betting exchange market. Although betting exchanges offer superior odds and returns to bettors, face less operational risk, have lower information costs and exhibit higher market efficiency, bookmakers continue to be successful. This ongoing success of bookmakers is surprising, as network externalities due to the migration of trading volume to the market with lower costs should lead to a consolidation into a single market structure (Madhavan, 2000).

In this paper we suggest a source of competitive advantage of the quote-driven market structure that has been neglected by the literature: the benefits arising from the continuous liquidity provision of the bookmaker. According to Demsetz (1968), a key function of market makers in financial markets is the supply of immediacy by continuously quoting prices and providing liquidity to the asynchronous arrival of orders from investors. In order-driven markets, however, liquidity is solely provided by the flow of orders from market participants and a lack of liquidity increases both transaction and waiting costs.

Using panel data of pairs of bookmaker and betting exchange odds for over 17,000 soccer matches played worldwide, we find that a major bookmaker offers more favorable odds than a major betting exchange until 6 hours before match start for *home win* bets and until 3.5 hours before match start for *away win* bets. Thereafter, the bookmaker offers less favorable odds. Hence, the bookmaker is more competitive during earlier stages of the pre-play period whereas the betting exchange is more competitive shortly before match start. Furthermore, we show that the price competitiveness of the betting exchange depends crucially on liquidity. The lack of liquidity leads to a lower price competitiveness at the order-driven market compared to the quote-driven market with unrestricted liquidity. Hence, the active management of quotes offers a distinct liquidity advantage.

This finding helps to explain the ongoing coexistence of the two market structures, as early betting volume should migrate to the more competitive bookmaker market. Moreover, our analysis sheds some light on the recent shift of financial markets into hybrid market structures where orders from individual traders compete with market makers. As market makers are particularly valuable when liquidity at the order book is low, hybrid structures combine the advantages of both the quote- and order-driven structure.

The third paper, *Does Bettor Sentiment affect Bookmaker Pricing?* (see Appendix A.3), examines the question of whether bookmakers exploit bettor sentiment by adjusting their odds accordingly. Analogous to sentimental investors in financial markets, sentimental bettors prefer bets with particular characteristics, e.g., bets on the team they support, and do not necessarily choose the bets with the highest expected return. Those preferences lead to an asymmetric volume demand even when the bookmakers' odds reflect the true winning probability of the underlying event. Bookmakers can react to asymmetric volume demand in three different ways: They can either lengthen or shorten the odds of the more heavily demanded bet or they can refrain from price adjustments and set unbiased odds that provide equal betting returns for all outcomes of the underlying event.

Unlike most previous studies, which rely on proxy measures for sentimental betting demand, we use actual bookmaker betting volume data to analyze the effect of bettor sentiment on bookmaker pricing. In particular, we investigate betting returns and volume percentages of the popular *over/under 2.5 goals* betting market on soccer matches. This market offers ideal research conditions. Because matches with a high number of total goals are generally more attractive than matches with few or no goals, bettors exhibit a natural preference for high match scores (Paul & Weinbach, 2002; Woodland & Woodland, 2010). At the same time, the empirical winning probability for either bet to win is close to 50%, because the average score of a soccer match lies between 2.4 and 2.6 goals (Norman, 2011). Therefore, potential risk considerations of bettors and bookmakers that could interfere with our results are negligible in this setting.

We find that the betting volume is highly concentrated on the *over 2.5 goals* bet, accounting for over 80% of the betting volume on average. However, this imbalance is not associated with systematic sentimental biases in bookmaker pricing and bettor returns. One possible explanation for this finding is that bettors can easily compare the odds listed by several different bookmakers, which increases the bettors' price sensitivity. Thus, small price changes tend to have a large impact on the betting volume and eventually on the bookmaker's profit. If a bookmaker shortens the odds of the *over 2.5 goals* bet, sentimental bettors would switch to a competitor. Otherwise, if a bookmaker lengthens the odds of the *over 2.5 goals* bet, he gains additional sentimental betting volume, however, at a higher risk of substantial losses.

This paper demonstrates that sentimental preferences are widespread in betting markets and bookmakers are well aware of their presence. However, as we are unable to detect a bias in the odds and thus fail to reject market efficiency, sentimental preferences do not necessarily reduce market efficiency if competition and price transparency are high.

The fourth paper, *Liquidity, Market Efficiency and the Influence of Noise Traders: Quasi-Experimental Evidence from the Betting Industry* (see Appendix A.4), investigates the effect of liquidity on market efficiency and the role of noise traders in the order-driven market. An understanding of the impact of liquidity on market efficiency has important implications for policy makers and regulators, whose actions affect liquidity. From a theoretical perspective, two hypotheses have evolved. On the one hand, liquidity could increase market efficiency due to lower transaction costs, which facilitates the elimination of mispricings (O'Hara, 1995). On the other hand, liquidity due to irrational noise traders could decrease market efficiency because rational agents are unable to fully offset noise traders' biases (De Long, Shleifer, Summers, & Waldmann, 1990). The aim of this paper is to test these competing hypotheses.

Empirical financial studies face two major limitations when investigating the relation between liquidity and market efficiency. First, fundamental values of traditional financial products are not observable, which hinders the measurement of market efficiency. Second, the amount of liquidity is an endogenous function of the pricing accuracy (Tetlock, 2008).

This paper contributes to the literature by investigating the relation between liquidity and market efficiency in the order-driven betting exchange *Betfair*. In this setting, the fundamental values of the betting contracts are revealed at a predetermined point in time and different minimum tick sizes create exogenous variation in liquidity. Moreover, we are able to test the influence of noise trader liquidity by analyzing the effect of liquidity on market efficiency for weekend and weekday matches separately. Earlier studies (e.g., Kopelman & Minkin, 1991; Sobel & Raines, 2003) have shown that betting activity at weekend matches is characterized by a higher share of irrational noise bettors than betting activity at weekday matches.

Using betting contracts on 2,227 soccer matches played in the *English Premier League* from 2006-2011 and in the *Spanish Primera Divisón* from 2009-2011, our results show that liquidity significantly decreases market efficiency for bets on weekend matches but not for bets on weekday matches. Therefore, our findings indicate that liquidity with a high fraction of noise bettors decreases market efficiency, whereas liquidity with a low fraction of noise bettors is not significantly related to market efficiency. As such, the type of liquidity seems to matter for market efficiency.

We have shown that noise trader liquidity can destabilize prices and harm market efficiency. Whereas the mispricing period in betting markets is limited by the end of the match, mispricing periods due to noise trader liquidity can last much longer in financial markets (De Long et al., 1990; Shleifer & Vishny, 1997). Thus, the risk of noise traders in harming market efficiency in financial markets might be even more severe than previously suggested.

Overall, this dissertation exploits the similarities between financial markets and betting markets while taking advantage of the unique peculiarities of the latter. From the analysis of this environment we draw important conclusions about the functioning of the quote-driven and the order-driven market structures. In particular, three major contributions to the literature arise from this dissertation.

First, the order-driven market structure exhibits higher market efficiency than the quote-driven market structure, which suggests that order-driven markets perform better in aggregating diverse information. However, quote-driven markets offer a distinct liquidity advantage that enables them to remain competitive against the order-driven structure. In periods when liquidity at the order-driven market is low, bid and ask quotations are wide apart. This results in high transaction costs and thus less competitive prices at the order-driven market compared to the quote-driven market. Our findings contribute as explanations of the ongoing coexistence of market structures and the tendency toward hybrid market structures that combine the advantages of the quote-driven and the order-driven structures.

Second, betting markets are characterized by the presence of strong sentimental preferences of bettors. However, even though the incoming betting volume demand is highly concentrated on one particular betting contract, we find that bookmakers offer unbiased odds and bettor returns. Hence, the presence of sentimental preferences does not necessarily translate into lower market efficiency as suggested by various previous studies.

Third, the type of liquidity seems to matter for market efficiency in the order-driven market structure where liquidity is provided entirely by market participants. Liquidity with a higher fraction of noise traders is found to harm market efficiency, whereas liquidity with a lower fraction of noise traders has no effect on market efficiency. Therefore, decisions of regulators and policy makers that increase market liquidity should take account of the possibility that additional liquidity may be characterized by noise traders whose entry into the market causes prices to diverge from fundamental values.

These studies using betting markets as a valuable test environment have enabled us to shed light on several open questions in the financial literature. Moreover, our findings lay the ground for future research in various directions.

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A Appendix: Papers included in this Dissertation

A.1

The Impact of Market Structures on Market Efficiency: Evidence from the Betting Industry*

Abstract

This paper investigates the impact of the market microstructure on market efficiency based on data from the betting industry. Similar to financial markets, betting markets are characterized by the coexistence of a quote-driven market structure (bookmakers) and an order-driven market structure (betting exchanges). We show that the quote-driven market exhibits lower market efficiency than the order-driven market. Taking advantage of the inefficient odds available at the quote-driven market leads to above-average, and in some cases even positive bettor returns.

JEL Classification: D40, G14

Keywords: Market Structure, Market Efficiency, Betting Market

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*This paper has been written jointly with Stephan Nüesch and Egon Franck.

1 Introduction

Worldwide, both quote-driven and order-driven market structures coexist in financial markets. In the quote-driven structure (dealer market), a market maker posts prices before order submission and takes the opposite side of each transaction. Specialists intermediate between buyers and sellers by posting the bid and ask price that they are willing to accept (Harris, 2003). In the order-driven structure (auction market), however, buy and sell orders are directly matched between investors. The order-driven system usually operates as a platform on which a continuous double auction process between individual traders is enabled. Hybrid market structures combine elements of both the quote-driven and the order-driven structure and allow orders from individual traders to compete with quotes from dealers (De Jong & Rindi, 2009).

The impact of the market structure on market efficiency is an ongoing debate in the market microstructure literature. Studies attempting to answer the question of whether intermediaries increase or decrease market efficiency in financial markets have produced weak and/or inconsistent results (Madhavan, 1992; Biais, 1993; Masulis & Shivakumar, 2002; Theissen, 2000; Bennett & Wei, 2006; Anand & Subrahmanyam, 2008). Empirical studies testing the comparative market efficiency across different market structures face two major difficulties. First, an objective benchmark against which a price can be evaluated is missing because the true fundamental value of an asset is not revealed within a finite time frame. Second, comparisons in the market microstructure are often accompanied by differences in underlying assets and/or different macroeconomic conditions.

We utilize the European betting industry to investigate the comparative market efficiency across order-driven and quote-driven market structures. Similar to financial markets, the betting industry likewise exhibits a coexistence of market structures. The traditional form of European gambling is bookmaker betting. In this structure, the bookmakers (e.g., *William Hill*, *Ladbrokes*) act as dealers posting the odds at which the bettors can place their bets. In recent years, betting exchanges have evolved as a popular alternative betting structure. Betting exchanges (e.g., *Betfair*, *Betdaq*) provide an electronic platform on which bettors can directly trade bets with each other. The European betting industry is particularly convenient for testing market efficiency across market structures, because the same betting contracts are traded in both quote-driven and order-driven market structures. Additionally, betting contracts are characterized by a well-defined termination point at which the true fundamental value is readily revealed (Vaughan Williams, 1999).

Previous studies that have addressed the comparative market efficiency of the different market structures concluded that the bookmaker market exhibits lower market efficiency than the betting exchange market (Smith, Paton, & Vaughan Williams, 2006, 2009; Franck, Verbeek, & Nüesch, 2010). However, these studies mainly investigated the market efficiency of the two markets separately and compared different goodness-of-fit measures across the two market structures. This paper provides a new test of the comparative market efficiency across market structures and uses a larger data set than any of the previous studies.

Using a sample of matched odds from several major bookmakers and the largest betting exchange *Betfair* for more than 9,500 games played in the top five European soccer leagues, we show that the betting exchange market outperforms the bookmaker market in terms of market efficiency. In particular, we find that the price difference between the two market structures contains relevant information, which is not fully captured in the bookmakers' odds. However, the betting exchange's odds already reflect the information contained in the price difference. Thus, the informational content of the odds is larger at the betting exchange than at the bookmaker market, implying that the order-driven market structure exhibits lower market efficiency. By taking advantage of the inefficient odds available at the quote-driven market, we conduct a simple betting strategy which leads to above-average, and in some cases even positive bettor returns.

Our paper proceeds as follows. Section 2 reviews the literature. Section 3 describes our data. Section 4 estimates the comparative efficiency based on the informational content of the price differences between the two market structures and tests a simple betting strategy. Section 5 concludes.

2 Literature Review

The hypothesis of market efficiency introduced by Fama (1991) states that current prices of assets fully reflect all available information. Within the market microstructure literature, this has raised the question of how market structure influences market efficiency. However, the findings are widely inconsistent. The theoretical model of Madhavan (1992) predicts that the quote-driven and the order-driven system are equally efficient with free entry into market making, whereas Biais (1993) concludes that dealer markets are less efficient than auction markets. As no direct measure of market efficiency is available, previous studies mainly focused on differences in market quality such as the bid-ask spread (Madhavan, 2000). Despite the challenging comparison due to different assets traded at each market structure or identical assets traded in different economic environments, the bid-ask spread, used as a measure of execution costs, has found to be generally lower in order-driven markets (e.g., De Jong, Nijman,

& Roell, 1995; Huang & Stoll, 1996, 2001). Other empirical studies address market efficiency explicitly. The study of Masulis and Shivakumar (2002) shows that prices of NASDAQ stocks (dealer market at that time) adjust quicker to new information than prices of NYSE stocks (auction market at that time). This is in line with the findings of Anand and Subrahmanyam (2008), who state that intermediaries in dealer markets contribute to better price discovery and market efficiency in financial markets. Contrariwise, Bennett and Wei (2006) show that market efficiency improves when stocks switch their listings from a dealer to an auction market. Moreover, Theissen (2000) compares auction and dealer markets within an experimental asset market. He concludes that asset prices in the continuous auction market are closer to the true value than prices in the dealer market.

Although tests of market efficiency across different market structures are much more convenient in betting markets than in financial markets (Vaughan Williams, 1999), only a limited number of studies have addressed the relative market efficiency in betting markets as yet.

Smith et al. (2006, 2009) compare traditional bookmaker odds and *Betfair* odds using UK horse racing data. They show that the favorite-longshot bias is stronger at the bookmaker market than at the betting exchange market. Franck et al. (2010) use odds information of 5,478 matches played in European soccer leagues to compare the market efficiency of bookmaker odds and betting exchange odds. They find that the betting exchange market provides more accurate predictions of a given event than the bookmaker market. This paper is the first to test whether price differences between the two markets have additional explanatory power on bettor returns beyond the bookmaker and betting exchange prices. In addition, we use a much larger data set than any of the previous studies.

3 Sample and Data

Our sample consists of 9,562 matches played in the top five European soccer leagues, namely in the *English Premier League*, *Spanish Primera Divisón*, *Italian Serie A*, *German Bundesliga* and *French Ligue 1*, during the six seasons from 2004/05 to 2009/10. For each match, we collect data on pre-play odds offered by the bookmakers *B365*, *Gamebookers*, *Interwetten*, *Ladbrokes*, *Sportingbet*, *Stan James*, *Victor Chandler* and *William Hill* from http://football-data.co.uk. These odds are recorded on Friday afternoon for weekend games and Tuesday afternoon for midweek games.

An obvious choice for the betting exchange is *Betfair*, because it is by far the largest and most liquid betting exchange. In the year 2010, *Betfair* had more than 3 million registered customers and processed more than 6 million transactions per day on average, more transactions than all European stock exchanges combined (Betfair, 2010). *Betfair's* liquidity is illustrated by the average volume per game of $6.5 million that was traded in the *English Premier League* over the 2009/2010 season. The *Betfair* data is taken from http://data.betfair.com and contains matched odds, traded volume and the number of bets on each team.

To approximate the time frame in which the bookmaker odds are taken, we calculate the volume-weighted odds for all odds matched by Friday or Tuesday afternoon.[1] Additionally, we calculate the volume traded and the number of bets settled by Friday or Tuesday afternoon. Finally, we record the actual outcome of each match to record whether a bet was successful or not.

A full sample of all matches played within these seasons would consist of 10,956 matches. Our dataset exhibits omissions due to the following reasons: First, either

[1]Even though we cannot merge the odds at exactly the same point of time, this should not affect our results, as pre-play price drifts within this short time frame are unlikely to be systematic.

bookmaker odds or *Betfair* odds are missing in our data source; such missing values seem to be sporadic and not systematically related to certain leagues, teams and seasons. As some bookmakers do not offer odds for all seasons considered, the sample size for an individual bookmaker ranges from 7,988 to 9,562 matches. Second, as the data is collected rather a long time before kick-off, some events exhibit low liquidity at *Betfair*. This may result in inaccurate odds and we drop all matches with a trading volume lower than £100. About 13% of matches are missing from our dataset for one of these two reasons.

The odds collected are quoted as decimal odds which denote the payoff of a successful bet. For example, if the odds quoted on the home team are 1.60, a one dollar wager pays $1.60 and yields a return of 60% if the home team wins. Therefore, higher odds imply a higher payoff in the case of success. However, the winning probability of such bets is correspondingly lower. For each bet i and bookmaker j we transform the quoted odds into prices by calculating

$$BM\_P_{i,j} = \frac{1}{odds_{i,BM_j}} \quad \text{and} \quad BF\_P_i = \frac{1}{odds_{i,BF,c}} = \frac{1}{(odds_{i,BF} - 1) \cdot (1 - c) + 1} \tag{1}$$

where BM denotes the bookmaker market and BF the betting exchange, respectively. We adjust the betting exchange odds by subtracting the standard *Betfair* commission c of 5% that is charged on net winnings. This makes the odds directly comparable to the bookmaker odds, which already include the bookmaker's margin. The prices of both market structures are now standardized between zero and one and indicate how much a bettor has to invest in order to collect $1 in the event of a successful bet (Forrest & Simmons, 2008). Put differently, the lower the price of a bet on the same outcome, the less a bettor has to pay for the chance of winning $1. We do not adjust these prices to ensure that they sum to one as suggested in previous studies (e.g., Forrest & Simmons, 2008; Franck et al., 2010). Such a margin correction assumes that the overround is distributed proportionally depending on the odds of the *home win*, *draw* and *away win* bets. However, if this is not the case, this procedure distorts the prices by construction. For example, if a bookmaker has a lower margin on the favorite team, a margin correction would lead to a self-induced favorite-longshot bias.[2] Figure 1 depicts the Kernel density of average bookmaker and *Betfair* prices. The

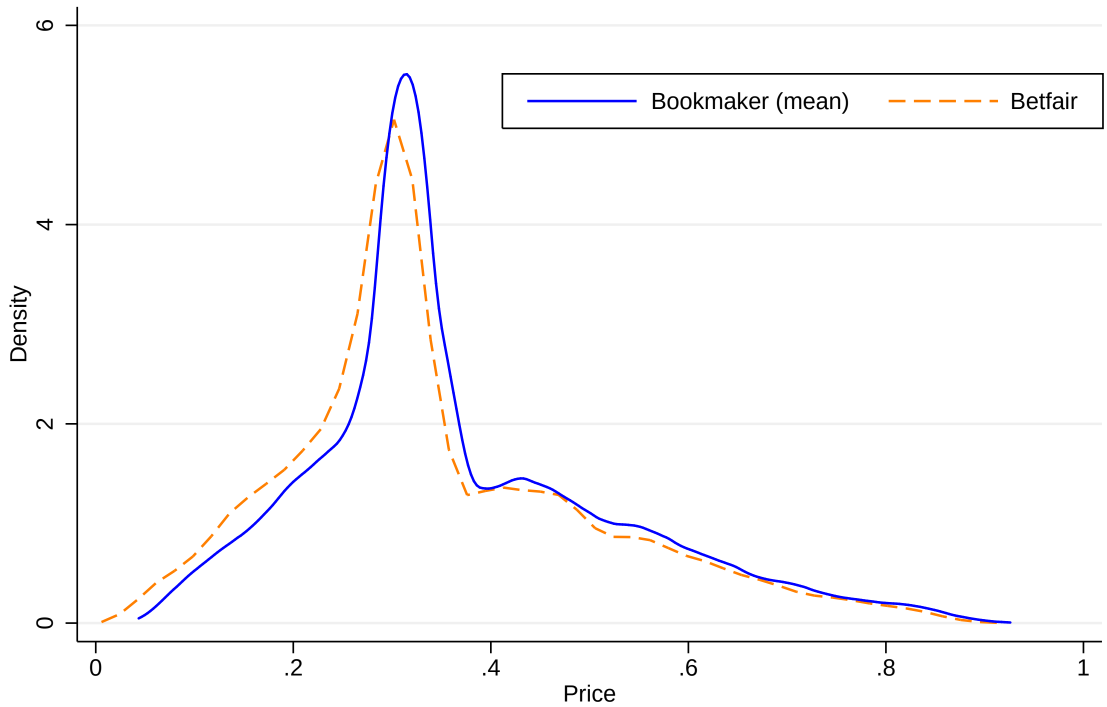

Figure 1: Kernel density of bookmaker and *Betfair* prices

average bookmaker's price density is shifted to the right, implying that less favorable odds (and therefore higher prices) are offered by the bookmaker in general. However, as the price (and thereby the winning probability) of a team increases, the prices of

[2] An estimation of our models based on margin corrected bookmaker odds does not change our findings. As expected, however, the effects tend to be even more pronounced.

the two market structures appear to be fairly close. The fact that price differences are related to price levels is puzzling, because we would expect that the price difference would be independent of the price level.

4 Price Deviations and Market Efficiency

Within this section two simple tests of comparative market efficiency across the quote-driven and the order-driven market are conducted. First, we test whether one market structure's price contains relevant information regarding the outcome that is not already included in the other market structure's price. Second, we test whether the information contained in the price deviation is able to substantially affect actual returns. Therefore, we take the price difference of the two market structures for the very same bet and test the informational content of this difference. In order to measure this price difference, we define for each bet i and bookmaker j the price ratio $PRATIO$ as

$$PRATIO_{i,j} = \frac{BM\_P_{i,j}}{BF\_P_i} \tag{2}$$

If the $PRATIO$ is > 1, the offered prices from bookmaker j are higher than the prices available at the betting exchange and vice versa. If the $PRATIO$ is equal to 1, the prices of the two market structures are identical. Simply stated, the lower this ratio, the better (i.e., lower) the bookmaker's prices. Figure 2 plots the price ratio from the average bookmaker price and the *Betfair* price against the mid-price of that bet, i.e., the price exactly midway between the *Betfair* price and the average of the bookmaker prices. The price differences vary systematically and are larger for low probability outcomes compared to high probability outcomes. To test market efficiency across the two market structures, we estimate several linear probability

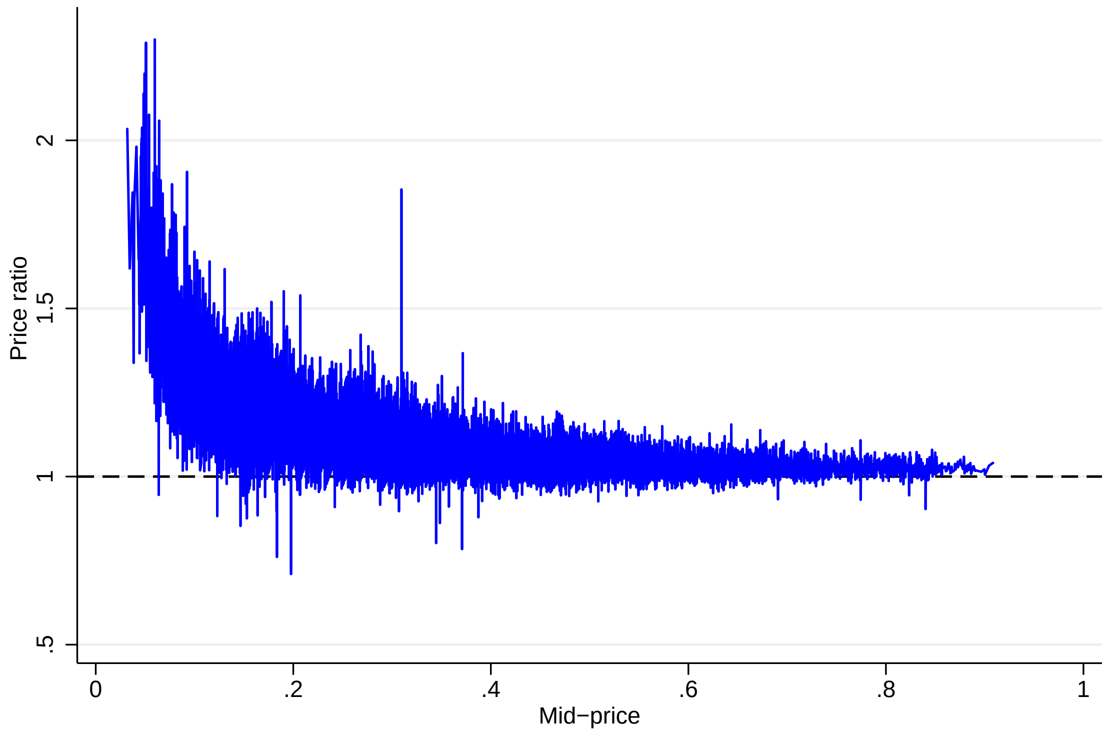

Figure 2: Price ratios across mid-prices

models using the actual outcome of a bet, which is either a win (1) or a loss (0), as the dependent variable.[3] We include the price of the corresponding market structure and the $PRATIO$ as independent variables. For the bookmaker market, we include the price of a randomly chosen bookmaker.[4] To ensure independence across observations, we estimate the model for *home win*, *draw* and *away win* bets separately. The results of these models are reported in Table 1. Column (1) shows that the coefficient of the $PRATIO$ variable is negative and statistically significant at the 0.1% level for *home win* bets. This implies that the price difference contains additional information which is not fully covered by the bookmaker price. By contrast, Column (2) suggests

[3]Alternatively, we also tested logit and probit models. All three specifications lead to the same conclusion.

[4]The main results are not sensitive to the random bookmaker specification. Estimations for each individual bookmaker lead to similar results.

Table 1: Price deviations and market efficiency

	Dependent variable: outcome (1/0)					
	Home win		Draw		Away win	
	(1)	(2)	(3)	(4)	(5)	(6)
random BM_P	0.960***		1.074***		0.973***	
	(0.031)		(0.105)		(0.034)	
BF_P		1.007***		1.194***		1.021***
		(0.032)		(0.115)		(0.035)
$PRATIO$	-0.326***	-0.058	-0.165**	0.090	-0.108***	-0.0001
	(0.063)	(0.067)	(0.061)	(0.073)	(0.023)	(0.024)
R^2	11.19%	11.24%	1.38%	1.41%	11.06%	11.23%
N	9,562	9,562	9,562	9,562	9,562	9,562

Notes: The table presents linear probability model estimates for the actual outcome of a bet (0/1). BM_P and BF_P reflect the prices by a random bookmaker and *Betfair*, respectively. The standard commission of 5% for betting exchange winnings is included in the prices. $PRATIO$ is defined as BM_P divided by BF_P. The bookmakers in the sample are Bet365, Gamebookers, Interwetten, Ladbrokes, Sportingbet, Stan James, Victor Chandler and William Hill. The heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 5%, 1% and 0.1% levels, respectively.

that $PRATIO$ has no explanatory power when the price of the betting exchange is included. At the bookmaker market, $PRATIO$ contains additional explanatory power beyond the bookmaker price, whereas the *Betfair* price already reflects the available relevant information contained in the price difference. The results for the *draw* bets specification in Columns (3) and (4) as well as the estimation results for *away win* bets of Columns (5) and (6) are in line with our results from *home win* bets. Therefore, the bookmaker market exhibits lower market efficiency than the order-driven betting exchange. About 11% of the variation in the outcome can be explained by the prices and the price difference for *home* and *away win* bets. The variation explained by the model is much lower for *draw* bets, which is in line with Dobson and Goddard (2001), who state that the *draw* appears to be a rather random event. Overall, the price difference has highly significant explanatory power in the quote-driven market, but no explanatory power in the order-driven market.

Our second test for the comparative market efficiency is an examination of returns. According to Vaughan Williams (1999), no historical information should systematically yield abnormal returns. This also implies that the price difference to the other market structure should have no effect on actual returns. Therefore, for each market structure we regress the ex-post returns on the ex-ante prices and the price ratios. The results are reported in Table 2. Again, we observe a consistent pattern for *home win*, *draw* and *away win* bets. Whereas at the betting exchange no variable affects the returns, higher values of $PRATIO$ significantly decrease the returns at the bookmaker market, documenting that the bookmaker prices are less informationally efficient.

Table 2: Effect of price deviations on returns

	Dependent variable: return					
	Home win		Draw		Away win	
	(1)	(2)	(3)	(4)	(5)	(6)
random BM_P	-0.091		0.634		0.265*	
	(0.102)		(0.404)		(0.128)	
BF_P		-0.063		0.872		0.235
		(0.114)		(0.496)		(0.150)
$PRATIO$	-1.035***	-0.384	-0.581**	0.306	-0.705***	-0.332
	(0.207)	(0.279)	(0.221)	(0.313)	(0.119)	(0.188)
R^2	0.51%	0.05%	0.17%	0.04%	0.80%	0.2%
N	9,562	9,562	9,562	9,562	9,562	9,562

Notes: The table presents regression estimates for the return on *home win*, *draw* and *away win* bets. BM_P and BF_P reflect the actual prices offered by a random bookmaker and *Betfair*, respectively. $PRATIO$ is defined as BM_P divided by BF_P. The standard commission of 5% for betting exchange winnings is included in the prices. The bookmakers in the sample are Bet365, Gamebookers, Interwetten, Ladbrokes, Sportingbet, Stan James, Victor Chandler and William Hill. The heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 5%, 1% and 0.1% levels, respectively.

Consequently, the results presented in this section suggest that the order-driven market is superior with respect to comparative market efficiency. We have shown that in the quote-driven market the price ratio provides valuable information for predicting the outcome as well as the actual returns of a bet. At the order-driven market however, this ratio provides no additional information for predicting either the outcome or the return of a bet.

To investigate how far bookmaker prices deviate from efficient prices, we conduct a simple betting strategy based on inter-market price deviations. Whenever a bookmaker offers a more favorable price than the betting exchange, we place a bet on this particular outcome at the best available bookmaker price. The expected returns of this strategy for *home* and *away win* bets are reported in Table 3.

Table 3: Simple betting strategy on price deviation

	Expected return	N	SE	t-statistic	p-value (t)
Home win	4.40%	1,481	0.027	1.62	0.053
Away win	-0.81%	855	0.048	-0.17	0.656

Notes: The table reports the expected returns of a simple betting strategy on outcomes for which the most attractive bookmaker offers more favorable prices than the betting exchange.

Based on our data, such a betting strategy would generate an expected return of 4.40% on *home win* bets and -0.81% on *away win* bets. Even though *away win* bets do no generate positive returns, they are still highly above the average return of -11.55% for a randomly placed *away win* bet.

5 Conclusion

This study uses the betting industry as a convenient laboratory for financial markets to contribute to the ongoing debate on the market efficiency of quote-driven and order-driven market structures. Whereas empirical tests on the comparative market efficiency of those two markets structures are complex in financial markets, this task is rather simple in betting markets. Because the true value of a bet is revealed after each match and identical bets on the same underlying match are available at both market structures, we are able to evaluate the comparative market efficiency. In particular, we test whether the price difference of the two markets provides additional information which is not already incorporated in the price offered. We show that the price difference, which is publicly available information, systematically predicts the outcome of a match at the quote-driven market, but not at the order-driven market. Similarly, the information contained in the price difference is valuable for generating abnormal returns at the quote-driven structure, but not at the order-driven structure. This clearly demonstrates the inferiority of the quote-driven structure compared to the order-driven structure in terms of market efficiency.

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A.2

The Liquidity Advantage of Quote-driven Markets: Evidence from the Betting Industry*

Abstract

This paper investigates the puzzling coexistence of the quote-driven market structure characterized by traditional bookmakers and the order-driven market structure characterized by betting exchanges in the betting industry. Even though betting exchanges are considered as the superior business model due to less operational risk and lower information costs, bookmakers continue to be successful. We show that liquidity, which is only guaranteed at the bookmaker market, significantly improves the bookmakers' price competitiveness. Using matched panel data of both bookmaker and betting exchange odds for over 17,000 soccer matches played worldwide, we find that a major bookmaker offers more favorable odds than a major betting exchange in the early pre-play betting period and less favorable odds shortly before match start.

JEL Classification: D40, L10, L83

Keywords: Market Structure, Market Performance, Liquidity, Betting Market

*This paper has been written jointly with Stephan Nüesch and Egon Franck.

1 Introduction

Since the beginning of the 2000s, the betting industry has been characterized by the coexistence of quote-driven and order-driven markets. Similar to intermediary market makers in quote-driven financial markets, bookmakers operate on their own account and quote betting odds at which bettors can place their bets (Croxson & Reade, 2011). In the order-driven market, betting exchanges serve as a market place where buy and sell orders are directly matched between bettors in a continuous double auction, without intermediaries (De Jong & Rindi, 2009).

This coexistence of market structures is puzzling. Even though betting exchanges offer superior odds and returns to bettors (Ozgit, 2005; Croxson & Reade, 2011), face less operational risk (Koning & van Velzen, 2009), have lower information costs (Davies, Pitt, Shapiro, & Watson, 2005) and exhibit higher prediction accuracy in their odds (Smith, Paton, & Vaughan Williams, 2006, 2009; Franck, Verbeek, & Nüesch, 2010), bookmakers continue to be successful. Namely, bookmakers have not only managed to survive but have also generated considerable growth in net revenues. For example *William Hill* and *Ladbrokes*, two major bookmakers in the United Kingdom, increased their net sportsbook revenues from £42m to £166.7m (+297%) and from £61.7m to £77.8m (+26%) respectively, between 2008 and 2012.

Previous studies have, either explicitly or implicitly, suggested several explanations of why bookmakers remain competitive. One explanation is that by actively managing quotes, bookmakers exploit bettor sentiment (e.g., Levitt, 2004; Forrest & Simmons, 2008; Franck, Verbeek, & Nüesch, 2011). The presence of sentimental bettors with preferences for bets with particular characteristics, e.g., betting on popular teams, results in an asymmetric volume demand. A bookmaker can exploit this sentiment by intentionally shading the odds for highly demanded bets and thereby increasing his profit. Furthermore, Franck, Verbeek, and Nüesch (2013) argue that because the identity of the bettors is known to the bookmakers, they are able to anticipate the future trading behavior of their customers. Therefore, bookmakers sometimes offer better odds than betting exchanges to acquire new customers. Once an account is opened with a bookmaker, bettors face switching costs to transfer their custom to a betting exchange and continue to place their bets at the bookmaker even under unfavorable conditions, which overcompensates the initial discount offered by the bookmaker. Croxson and Reade (2011) argue that learning costs from the new interface of betting exchanges and efforts undertaken by bookmakers to retain their customers provide a plausible explanation for the continuing survival of bookmakers. Finally, Ozgit (2005) provides an order-size explanation. By analyzing the limit order book of a betting exchange, he observes that execution costs rise sharply and that the higher returns vanish as the order size gets larger. Thus, bettors with high bankrolls will prefer to place their bets with bookmakers.

In this paper we suggest the liquidity advantage of the quote-driven bookmaker market as an alternative explanation for the coexistence of both market structures. In particular we test how liquidity affects the relative competitiveness of the bookmaker market and the betting exchange market.

From a theoretical perspective, Demsetz (1968) argues that a crucial role of the market maker in a quote-driven financial market is the continuous provision of liquidity. By guaranteeing market liquidity at the prices quoted, the market maker fills the gap that arises from asynchronous order arrival of buyers and sellers. Hence, the market maker facilitates the rapidity of exchange by offering narrow bid-ask spreads. In order-driven markets, however, liquidity is provided by the flow of orders from market participants (De Jong & Rindi, 2009). Here, a lack of liquidity due to an absence of two-sided trading interest or asynchronously arriving orders might result in bid and ask prices that are far apart. In such periods, order-driven markets perform poorly as transaction costs increase due to wide jumps in prices (Demsetz, 1968).

Unlike previous studies (e.g., Ozgit, 2005; Franck et al., 2010; Croxson & Reade, 2011) that compared the odds from top-division leagues or large tournaments collected at a single point in time shortly before match start, this paper uses an extensive panel data set. The data covers over 17,000 soccer matches played worldwide with odds information from the bookmaker *Tipico* and the betting exchange *Betfair* over the 72 hours before match start. We find that bookmaker odds are significantly higher than betting exchange odds until 6 hours before match start for *home win* bets and until 3.5 hours before match start for *away win* bets. Thereafter, the bookmaker odds are significantly lower. Thus, the bookmaker is more competitive during earlier stages of the pre-play period whereas the betting exchange is more competitive shortly before match start.

The liquidity at the betting exchange significantly affects the odds differences. High liquidity at the betting exchange decreases the relative price competitiveness of the quote-driven market. However, if liquidity at the betting exchange is low, the quote-driven bookmaker market offers more favorable odds. Hence, the lack of liquidity leads to a lower price competitiveness at the order-driven market compared to the quote-driven market with unrestricted liquidity. Our findings are robust to a subsample analysis that considers only matches played in the 10 most popular leagues in the world, which are likely to attract a lion's share of the total betting volume.

Our evidence for the liquidity advantage of quote-driven market structures in the betting industry provides an additional explanation of the coexistence of bookmakers and betting exchanges. The liquidity advantage also rationalizes the decision of *Betfair* to start offering quoted odds in addition to the exchange based odds as of February 2013 (Betfair, 2013a). Our findings also help to explain the recent shift in financial market structures from pure quote-driven or pure order-driven structures into hybrid structures which combine the advantages of both models.

The remainder of this paper is organized as follows. In Section 2, we discuss the two market structures in the betting industry in more detail and review the relevant theoretical and empirical literature. In Section 3, we describe our data set containing odds of soccer matches available over the 72 hours before match start. Section 4 presents the empirical analysis of the differences in price competitiveness between the two market structures. Section 5 concludes.

2 The Betting Industry

Similar to conventional assets and derivatives in financial markets, a bet is a state-contingent contractual claim on some future cash flow. This cash flow is determined by two parameters: (i) the outcome of the underlying event, such as a horse race, a soccer match or a political election, and (ii) the price of the contract, i.e., the posted odds (Sauer, 1998). Currently, the most common betting type is fixed-odds betting where the cash flow of a successful bet is determined ax-ante. For example, if the decimal odds on the home team of a soccer match are 1.40, a one dollar wager pays \$1.40 and yields a return of 40% if the home team wins. Therefore, higher odds imply a higher payoff in the case of success but an accordingly lower winning probability.

Traditionally, betting markets were operated by bookmakers. Similar to market makers in financial markets, bookmakers serve as intermediaries between buyers (bettors willing to place a bet on a particular outcome) and sellers (bettors willing to place a bet on the opposite outcome). The bookmakers unilaterally determine the odds (i.e., the price) for a given betting contract at which they are willing to accept bets (Harris, 2003). In this market, the bookmakers supply all the liquidity and the transparency regarding the trading process is rather low as only the odds are publicly known (De Jong & Rindi, 2009). The odds quoted by the bookmakers already contain a commission or 'overround' which compensates them for providing liquidity and bearing the risk of unfavorable outcomes. Examples of well-established bookmakers are *Bwin*, *Ladbrokes*, *Tipico* and *William Hill*.

Since 2000, betting exchanges have evolved in the betting industry. They operate as order-driven markets, where buyers and sellers trade directly with each other in a continuous double auction without the intermediation of market makers. In this market structure, bettors can provide or take liquidity. Bettors who provide liquidity post a limit order which indicates the terms at which they will trade. However, the execution takes place only if there is a corresponding order on the opposite side of the market. Otherwise, the limit order is placed in the limit order book until it is either executed or canceled. Bettors who take liquidity submit a market order which is immediately executed at the best odds available (Harris, 2003; De Jong & Rindi, 2009). The transparency is higher at betting exchanges, as the limit order book is publicly known and the trading volume as well as the last traded odds are recorded. Betting exchanges facilitate trading activity by providing an electronic platform on which supply and demand is matched and collect a commission on the net winnings of successful bets (Franck et al., 2013). Examples of larger betting exchanges are *Betfair*, *Betdaq* and *World Bet Exchange*.

Earlier studies which compare the two market structures suggest that the betting exchange market is superior to the traditional bookmaking market in several ways. Koning and van Velzen (2009) argue that a fundamental advantage of betting exchanges is that they do not take any trading position. Because betting exchanges just charge the winners a certain commission, a steady flow of income independent from the match outcomes is guaranteed. This exposes betting exchanges to minimal risk. In contrast, traditional bookmakers are continuously exposed to risk and lose on some events when they misjudge the probabilities or when they are over-exposed to the event that occurs (Davies et al., 2005). Furthermore, bookmakers need informed specialists who monitor the market and actively manage the odds. Therefore, the information costs of the bookmakers are considerably higher than those of betting exchanges, which simply provide the trading platform (Davies et al., 2005).

The study of Ozgit (2005) investigates bookmaker and betting exchange odds of 623 matches from the National Basketball Association (NBA) and finds that the net returns of bettors at the exchange are consistently higher. Similarly, Croxson and Reade (2011) compare the odds from both market structures during 22 matches of the Euro 2008 soccer championship and find superior returns at the betting exchange.

Moreover, Croxson and Reade (2011) show that the betting exchange provides more accurate odds in terms of information efficiency than the bookmaker. Using UK horse racing data, Smith et al. (2006) as well as Smith et al. (2009) compare the odds from the betting exchange *Betfair* with odds from traditional bookmakers. They find that betting exchange odds have more predictive value than the corresponding bookmaker odds and exhibit a lower favorite-longshot bias[5]. The study of Franck et al. (2010) compares the prediction accuracy of the odds from eight different bookmakers to the corresponding betting exchange odds from *Betfair* on soccer matches played

[5]The favorite-longshot bias is the well-documented empirical regularity that favorites win more often than implied by their odds and longshots win less often (Cain, Law, & Peel, 2000).

in the top five European leagues. In line with the previous literature, the results of a univariate probit regression and several goodness-of-fit measures reveal a clear superiority of the betting exchange over the bookmaker market.

Given the arguments elaborated above, the ongoing success of the quote-driven bookmaker structure is surprising. Madhavan (2000) argues that network externalities due to the migration of trading volume to the market with lower costs should lead to a consolidation into a single market structure. However, there are also some arguments in the literature highlighting certain competitive advantages of the quote-driven market structure.

One advantage of actively managed odds is rooted in the bookmaker's profit maximizing response to incoming betting demand. When the incoming volume demand is asymmetrically distributed due to sentimental preferences of bettors, bookmakers can increase their profits by distorting their odds. Levitt (2004) demonstrates that bettors have a systematic preference for favorite teams and shows that a monopolistic bookmaker for NFL games can substantially increase his profits by shortening the odds for bets with a higher demand. By contrast, Forrest and Simmons (2008) and Franck et al. (2011) find that bookmakers offer more favorable odds for bets on popular teams. They argue that because demand in European betting is likely to be elastic, a risk-neutral bookmaker is able to increase his profit by trading off margins against the attraction of additional betting revenues. Whether bookmakers are able to exploit bettor sentiment seems to depend on the betting environment. A recent study of Flepp, Nüesch, and Franck (2014), for example, shows that bookmakers are not exploiting bettor sentiment in the over/under 2.5 goals betting market, even though the betting volume is highly concentrated on the *over* bet. In this setting, where risk considerations of bettors and bookmakers are negligible, bookmakers offer equal returns for both outcomes and collect their margins accordingly. Likewise, Page (2009) does not find any evidence of biased odds due to bettor sentiment.

Another advantage of the bookmaker market is the knowledge of the participants' identity. According to Franck et al. (2013), this allows bookmakers to take the expected future trading behavior of their customers into account. Therefore, bookmakers sometimes offer over-favorable odds as an element of their promotional activities to attract new customers. Once bettors have opened an account, they tend to stick with the given bookmaker even under unfavorable conditions. This pays off the initial 'loss leader' bet offered by the bookmaker. The intentionally distorted odds of the bookmaker exhibit lower information efficiency than exchange-based odds, which results in inter-market arbitrage opportunities in 19.2% of the matches in the top five European soccer leagues considered.

Croxson and Reade (2011) hypothesize that bookmakers continue to be successful because bettors face learning costs when switching to the betting exchange structure. The exchange interface, with its limit order book, different odds and the options to back (i.e., betting on a certain outcome) or lay (i.e., betting against a certain outcome) a bet, may discourage bettors who are used to betting at a traditional bookmaker. At the same time bookmakers offer incentives like free bets to dissuade customers from leaving.

Ozgit (2005) provides a trade-size explanation. He argues that the superior net returns found at the betting exchange do not account for the size of the wagers. He finds that large wagers exceed the volume available at the best odds in the limit order book. Thus, the remaining amount of the wager is executed at the second best or third best odds, which eliminates the higher returns rapidly.

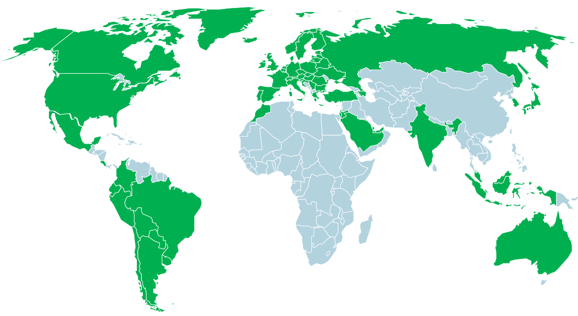
In this paper, we investigate a different source of competitive advantage for the quote-driven market structure: the benefit arising from the continuous liquidity provision of the bookmaker. According to Demsetz (1968), a key function of market makers in financial markets is the supply of immediacy by continuously quoting prices and providing liquidity to the asynchronous arrival of orders from investors. This presence reduces temporal imbalances in order flow and increases the rapidity of exchange. By contrast, a lack of liquidity at the order-driven structure normally provided by the flow of orders from market participants leads to relatively high bid quotations and relatively low ask quotations, which increases both transaction and waiting costs.

3 Sample and Data

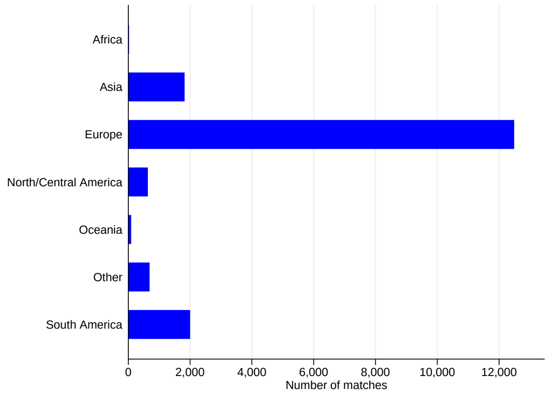
Our data set consists of decimal betting odds from the bookmaker *Tipico* and the betting exchange *Betfair* on the *winner* betting contracts on *home win*, *draw* and *away win* of soccer matches. *Tipico* is one of the leading bookmakers in Europe. Through its online portal and more than 1,000 betting shops across Europe, the company offered odds on 1.76 million betting contracts and handled over 790 million bets from customers in 2012 (Tipico Co. Ltd., 2013). *Betfair* is the largest and most liquid betting exchange. In 2012, the betting exchange had over 4 million registered customers and processed more than 7 million transactions on an average day, which is more than the transactions of all European stock exchanges combined (Betfair, 2012).

The data is provided by *Tipico* and covers 17,689 matches from over 400 leagues across more than 60 countries played between March 2012 and October 2012. Figure 1a highlights the countries represented in the data. Within each country, we observe matches from different divisions. For example, data from England includes matches from the *Premier League* (level 1), *Championship* (level 2), *League One* (level

3), *League Two* (level 4), *Conference National* (level 5) and *Conference North/South* (level 6) are available. Additionally, transnational tournaments such as the UEFA Champions League or Europa League, World Cup qualification matches or international friendly matches are also covered by the data set. Figure 1b displays the distribution of matches across continents. The lion's share of matches was played in European leagues, accounting for over 12,000 matches.



(a) Countries covered by the data set



(b) Number of matches across continents

Figure 1: Match coverage across countries and continents

We observed the decimal odds during the 72 hours before match start.[6] The odds information of the bookmaker and the betting exchange is taken simultaneously and the time of collection is recorded accurately to the second. The frequency at which the odds were collected depended on the time remaining until match start, ranging from every 3 hours between 72 and 48 hours before match start to every 5 minutes during the final 3 hours before match start. Table 1 shows the complete algorithm according to which the odds information was collected. Normally, the actual time point of the odds collection differs slightly from the defined algorithm. We round

[6]As not all matches have odds data available as early as 72 hours before play, a higher number of matches are observed at shorter times before match start. For 72 hours before match start, we observed 5,724 matches and at match start we observed 17,689 matches.

Table 1: Odds collection algorithm

Hours before match start	72-48	48-15	15-6	6-3	3-0
Time between odds observations	3 hours	1 hour	15 minutes	10 minutes	5 minutes

Notes: The table shows the odds collection frequency algorithm according to which odds information has been recorded.

those observation to the nearest timestamp according to the algorithm in order to equalize all timestamps across the matches in the dataset.[7]

Figure 2 displays the odds information available for the *home win* bet from the match of *Liverpool* vs. *Manchester United* played on September 23, 2012, clearly showing how the frequency of observations increases as the time before match start diminishes. This systematic applies to all matches in our dataset. In this example, the bookmaker changes his quoted odds only once, whereas the odds available at *Betfair* exhibit a higher variation. This pattern is typical for many matches in our data set: while the bookmaker changes his odds about twice on average, the betting exchange odds change about 31 times on average.

In total, we observe 1,875,430 pairs of odds from the bookmaker and the betting exchange for each of the three events *home win*, *draw* and *away win*. Additionally, the data set contains the cumulative trading volume per match at the betting exchange.

To accommodate differences between more and less heavily demanded matches we form a subsample consisting of matches played only in the top 10 soccer leagues in the world. These leagues include the *1. Bundesliga* (Germany), *Premier League* (England), *La Liga* (Spain), *Serie A* (Italy), *Serie A* (Brazil), *Liga MX* (Mexico), *MLS* (USA), *Eredivisie* (Netherlands), *Ligue 1* (France) and the *Primera Division*

[7]Note that this rounding procedure only affects the time point of the odds collection. The original timestamps of *Tipico* and *Betfair* data are identical. For example, if the original timestamp is 48h2m31s before match start, the timstamp for this data pair is rounded to 48h0m0s.

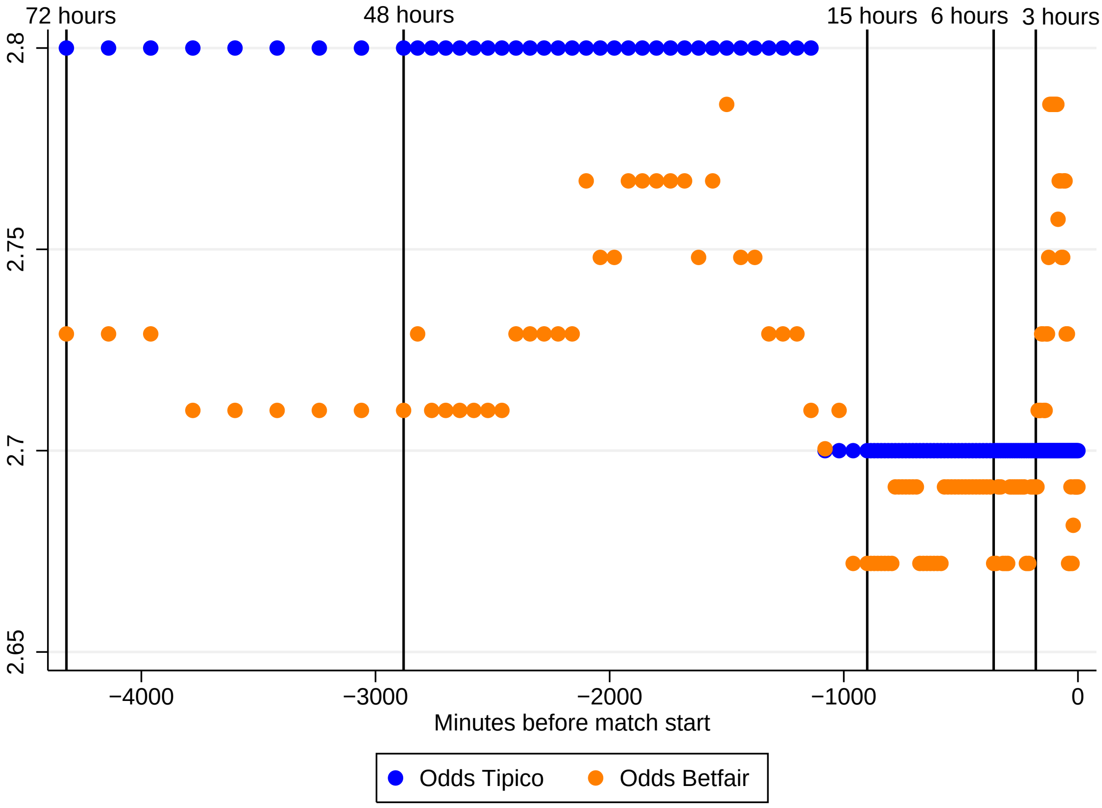


Figure 2: Decimal odds on *home win* bet (Liverpool vs. Manchester United, September 23, 2012)

(Argentina) (World Soccer, 2013). Matches played within those popular leagues are likely to attract substantially higher betting volume at both market structures due to a larger fan base, television broadcasts or media presence, for example. This subsample consists of 1,441 matches, leading to 181,084 pairs of odds-observations from the bookmaker and the betting exchange over the three-day period.

4 Empirical Analysis

Previous studies primarily relied on the comparison of odds from top-division leagues and large tournaments collected at a single point in time shortly before match start.

Our data set permits us to analyze the dynamics of price competitiveness over the 72 hours before match start and over a large scope of different leagues. We begin our empirical analysis by assessing the relative competitiveness of the bookmaker and the betting exchange market over time and proceed by studying the role of liquidity in explaining the differences in price competitiveness.

4.1 Price Competitiveness

Our measurement of price competitiveness is based on the objective benchmark of the odds. As identical betting contracts are offered on both market structures simultaneously, better odds should attract a higher number of bettors, ceteris paribus (Pope & Peel, 1989; Croxson & Reade, 2011). For the ease of interpretation, we convert the decimal odds into prices, which are the reciprocal of the decimal odds (e.g., $p = \frac{1}{1.40} \approx 0.714$). These prices represent the amount of money a bettor has to invest in order to collect \$1 for a winning bet (Forrest & Simmons, 2008). Hence, a lower price for an identical betting contract is superior to a higher price.

In the bookmaker market, the commission is already included in the odds quoted by the bookmaker. For each match i, event $e \in \{home\ win,\ draw,\ away\ win\}$ and time t before match start, the price offered by the bookmaker is defined as

$$p_{iet,BM} = \frac{1}{odds_{iet,BM}} \tag{1}$$

where $odds_{BM}$ refers to the decimal odds quoted by the bookmaker. Betting exchanges usually charge a commission on net winnings that is not included in the odds offered. Hence, the net price at the betting exchange is calculated as

$$p_{iet,BE} = \frac{1}{\left[\underbrace{(odds^{back}_{iet,BE} - 1)}_{\text{net winnings}} \cdot (1 - c)\right] + 1} \tag{2}$$

where $odds^{back}_{BE}$ refers to the best decimal back odds, i.e., the odds of a bet on a certain outcome, available at the betting exchange and c refers to the commission. The commission at *Betfair* varies between 2% and 5% on net winnings, contingent on the betting activity of a bettor. Thereby, the commission decreases the more money a bettor has wagered in the past (Betfair, 2013b). In this paper, we employ the standard commission of 5% to compute a lower bound for the net returns from *Betfair*.[8]

At each point in time, the prices from the two market structures are collected simultaneously. Therefore, we start our analysis by conducting a nonparametric Wilcoxon signed-rank test of the net prices. Panel A of Table 2 reports the results for prices collected 72 hours before match start for the *home win*, *draw* and *away win* events separately. For all three events, the prices offered by the bookmaker are significantly lower than the prices offered by the betting exchange. Thus, the bookmaker offers a superior product to bettors at this point in time. The difference in prices is considerable. On the *home win* event for example, the average prices from bookmaker and the betting exchange are 0.469 and 0.510, respectively which results in an additional average payout of the bookmaker to bettors of $0.17 for every dollar invested in case

[8] It is reasonable to assume that most of the bettors betting at *Betfair* are paying 5% in commission, as a discount in the commission requires very high betting activity. According to the *Betfair* commission rule, a bettor has to wager at least $112,500 per week in order to reach the 2% commission rate (Betfair, 2013b).

Table 2: Comparison of net prices

Panel A: Wilcoxon signed-rank test of net prices 72 hours before match start

	Home win			Draw			Away win		
	p_{BM}	p_{BE}	z	p_{BM}	p_{BE}	z	p_{BM}	p_{BE}	z
Mean	0.469	0.510	-25.7***	0.288	0.333	-30.3***	0.319	0.365	-20.7***
SD	0.152	0.181		0.039	0.136		0.137	0.199	
N	5,724	5,724		5,724	5,724		5,724	5,724	

Panel B: Wilcoxon signed-rank test of net prices at match start

	Home win			Draw			Away win		
	p_{BM}	p_{BE}	z	p_{BM}	p_{BE}	z	p_{BM}	p_{BE}	z
Mean	0.483	0.473	56.3***	0.277	0.268	67.4***	0.331	0.324	54.2***
SD	0.176	0.175		0.046	0.059		0.164	0.167	
N	17,689	17,689		17,689	17,689		17,689		

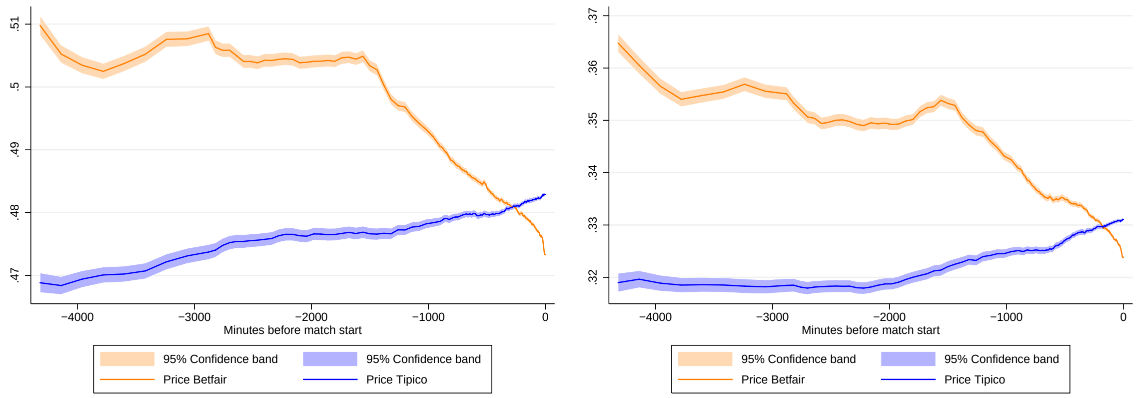
Notes: The table presents the results of a nonparametric Wilcoxon signed-rank test on the difference in net prices from the bookmaker (p_{BM}) and the betting exchange (p_{BE}) indicated by the z-statistic. Panel A shows the results three days before match start. Panel B shows the results at match start. In all tests, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

of a successful bet.[9] This results contradicts the findings from previous studies which imply that prices from the betting exchange are always superior.

Panel B of Table 2 compares the prices at match start. Now, the prices offered at the betting exchange are clearly superior to the prices offered by the bookmaker. This finding is consistent for all three events within a match. The results from Table 2 provide first evidence that the prices offered by the bookmaker are competitive in earlier stages of the pre-play betting period but not at match start.

To get a complete picture of the dynamic of price competitiveness we test the difference in prices for each point in time available in the data set over the 72 hours before match start. Figure 3 shows the average prices over time including 95% con-

[9] $\Delta return = return_{BM} - return_{BE} = \left[\left(\frac{1}{p_{BM}}\right) - 1\right] - \left[\left(\frac{1}{p_{BE}}\right) - 1\right] = \left[\left(\frac{1}{0.469}\right) - 1\right] - \left[\left(\frac{1}{0.510}\right) - 1\right] \approx 0.17$



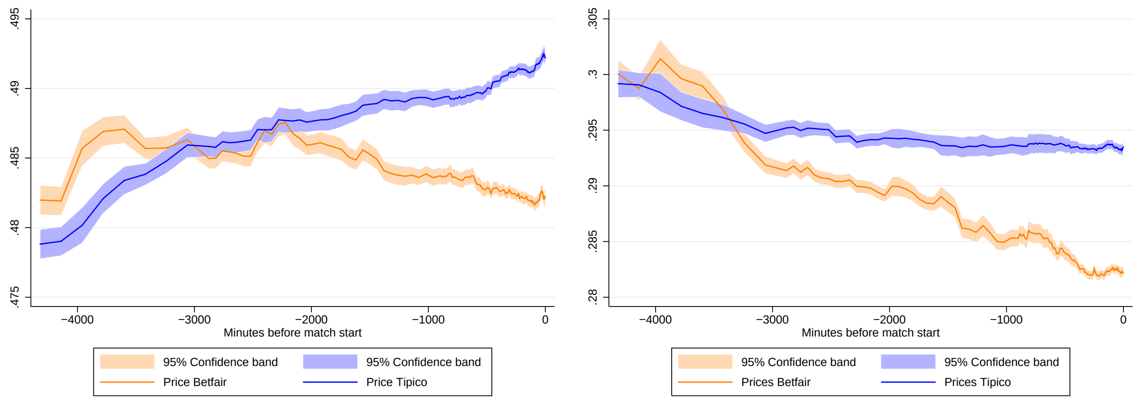
(a) Home win (b) Away win

Figure 3: Prices from the bookmaker and the betting exchange over time (all leagues)

fidence bands resulting from simple t-tests. The bookmaker's prices are consistently more attractive over a long period of time during earlier stages in the pre-play period. For the *home win* event (Figure 3a), the average prices of the bookmaker continue to be significantly lower until about 6 hours before match start. During the 6 hours before match start, the prices from the betting exchange improve dramatically and offer better value than the bookmaker prices. A similar picture arises for the *away win* event depicted in Figure 3b, with the switching point of price competitiveness taking place about 3.5 hours before match start. The results for the *draw* event are similar with a switching point of 3.3 hours before match start.

In a robustness check, we compare the net returns to bettors over time as an alternative measure of price competitiveness. Again, we find that the bookmaker market is more competitive in earlier betting periods, whereas the betting exchange market offers superior value shortly before match start.

Next, we investigate the comparative price competitiveness within the subsample of popular matches from the top 10 leagues worldwide. Price competitiveness is crucial for these matches, because they attract a large share of the betting volume on soccer matches. Figure 4 displays the net prices over time for matches played in the top 10 leagues. Again, the prices for the *home win* event (Figure 4a) are significantly lower at the bookmaker market in the early betting period but higher in the later betting period compared to the prices from the betting exchange. The switching point, however, is shifted in time, with prices being superior at the betting exchange from 34 hours before match start. A similar conclusion is drawn from the *draw* event with a switching point at 47 hours before match start. For the *away win*



(a) Home win

(b) Away win

Figure 4: Prices from the bookmaker and the betting exchange over time (top 10 leagues)

event (Figure 4b) the betting exchange prices are superior from 54 hours before match start. Before this point of time, the bookmaker prices are lower than betting exchange prices, however, the difference is not statistically significant.

Overall, a clear picture emerges from the comparison of the average net prices over time. The bookmaker offers lower and thus more favorable prices to bettors in earlier stages of the pre-play betting period. The price advantage of the bookmaker is considerable, lasting on average until 6 hours before match start for *home win* bets and until 3.5 hours before match start for *away win* bets, respectively. Even for matches played only in the top 10 leagues worldwide, the bookmaker price remains competitive, although the switching point at which betting exchange prices become superior occurs much earlier before match start. As such, bettors who do not want to wait until shortly before match start to place their bets are better off betting at the bookmaker market on average.

4.2 Liquidity Provision

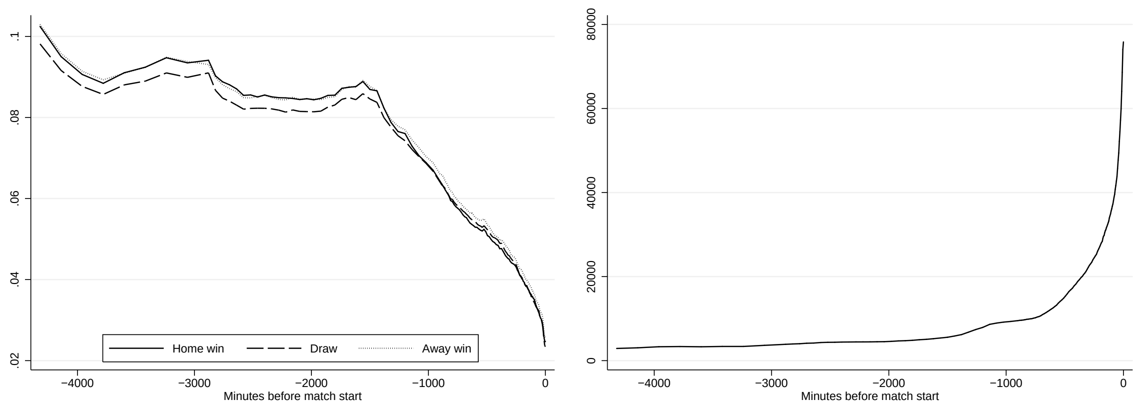
Having considered the price competitiveness of the quote-driven bookmaker market and the order-driven betting exchange, we proceed by studying the role of liquidity as a moderating factor in explaining the dynamics of price competitiveness over time. Liquidity is an important characteristic of well-functioning markets and permits the trading of large quantities quickly at low costs (Harris, 2003). While liquidity in the quote-driven market is guaranteed by the bookmaker, liquidity in the order-driven market depends on the flow of orders from market participants (De Jong & Rindi, 2009). Hence, we concentrate on the development of betting exchange liquidity because a lack of liquidity in the order-driven market could affect the cost of immediacy and thus the price competitiveness (Demsetz, 1968).

A common measure of liquidity in financial studies is the quoted spread (e.g., Amihud & Mendelson, 1986). The quoted spread is the difference between the lowest ask price and the highest bid price (Chordia, Roll, & Subrahmanyam, 2008). A small quoted spread indicates high market liquidity, because the transaction costs are lower. We calculate the quoted spread ($QSPR$) as

$$QSPR_{iet,BE} = \frac{1}{odds^{back}_{iet,BE}} - \frac{1}{odds^{lay}_{iet,BE}} \tag{3}$$

where $odds^{back}$ refers to the best ask price and $odds^{lay}$ to the best bid price available at the betting exchange.

Another measure of liquidity employed in the literature is the trading volume (Chordia, Roll, & Subrahmanyam, 2001). Thus, we use the cumulative trading volume (VOL) per match as basis for our second liquidity proxy. Figure 5a displays the development of liquidity based on the average quoted spread over the 72 hours before match start for the three events separately. Interestingly, the quoted spreads



(a) Average quoted spread ($QSPR$) (b) Average trading volume (VOL)

Figure 5: Betting exchange liquidity over time

remain relatively stable until around 24 hours before match start. Thereafter, they fall sharply, from an average quoted spread of 0.086 at 24 hours before match start to 0.025 at match start. A similar pictures arises for the liquidity based on the cumulative trading volume over time (see Figure 5b). The trading volume remains low until around 24 hours before match start and increases exponentially thereafter. Given this evolution of the trading volume, we use the logarithmized cumulative trading volume ($LnVOL$) in our further analysis.

To investigate the relative price competitiveness we take the difference between the bookmaker price and the betting exchange price offered at each point in time and define this difference Δp as

$$\Delta p_{iet} = p_{iet,BM} - p_{iet,BE} \tag{4}$$

A positive value of Δp indicates that the bookmaker offers a higher price and is less competitive than the betting exchange. Conversely, a negative value of Δp indicates that the bookmaker market offers a lower price and is more competitive.

To examine the link between price competitiveness and liquidity, we estimate for each event e the following fixed effects panel model

$$\Delta p_{it} = \alpha_i + \beta_1 \cdot Liquidity_{it} + \beta \cdot \Gamma_{it} + \epsilon_{it} \tag{5}$$

where *Liquidity* is either measured by the quoted spread ($QSPR$) or by the logarithmized trading volume ($LnVOL$). To capture a possible time trend in the data we include a set of hourly dummies (Γ) in the model. This allows us to control for any time-related price differences in a flexible way. The constant α_i controls for time-constant differences across matches.

The estimation results based on standard errors corrected for heteroskedasticity and autocorrelation are presented in Table 3. Columns (1), (3) and (5) of Table 3 report the coefficients for the quoted spread of the *home win*, *draw* and *away win* events, respectively. All three coefficients are negative on the 1% significance level. We

Table 3: Fixed effects panel analysis of price differences (all leagues)

	Dependent variable: Δp					
	Home win		Draw		Away win	
	(1)	(2)	(3)	(4)	(5)	(6)
$QSPR$	-0.562***		-0.696***		-0.688***	
	(0.005)		(0.003)		(0.005)	
$LnVOL$		0.003***		0.005***		0.004***
		(0.0003)		(0.0003)		(0.0003)
Hourly dummies	Yes	Yes	Yes	Yes	Yes	Yes
$F(56, 17{,}672)$	492.78***	70.81***	1614.96***	74.21***	745.50***	63.66***
R^2 overall	70.37%	10.21%	88.42%	13.40%	78.11%	10.69%
N	1,857,741	1,857,741	1,857,741	1,857,741	1,857,741	1,857,741
N of groups	17,673	17,673	17,673	17,673	17,673	17,673

Notes: The table reports the coefficients estimated from a fixed effects panel model with standard errors corrected for heteroskedasticity and autocorrelation. Standard errors are reported in parentheses. The dependent variable is the price difference Δp between the two market structures. Matches from all leagues in the data set are included for the estimation. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

find that illiquidity (i.e., a higher quoted spread) significantly decreases the relative price competitiveness at the betting exchange market. Columns (2), (4) and (6) of Table 3 report the estimated coefficients for the trading volume. For each of the three events, we find a positive effect of liquidity on the price difference, indicating an improvement of the price competitiveness at the betting exchange relative to the bookmaker market. In all models, dummy variables for each hour within the 72-hour period control for a potential general time trend which could affect the price differences.

Taken together, our findings imply that higher liquidity is associated with higher price competitiveness at the betting exchange. In periods where liquidity is low at the betting exchange, however, the guaranteed liquidity provision at the bookmaker market leads to significantly more favorable prices.

In order to investigate the robustness of our results we include the bookmaker price $p_{it,BM}$ in Equation (5) as a control variable. The reasoning behind this is that changes in the bookmaker price might influence the relation between liquidity and the price difference. However, the previous findings do not change in any significant way. Additionally, an estimation of Equation (5) with the difference between the net returns to bettors from both market structures as dependent variable leads to the same conclusion.

We extend our analysis by studying the effect of liquidity provision on price competitiveness on the subsample consisting of matches from the top 10 leagues worldwide. The estimated coefficients are presented in Table 4. The results from this estimation are statistically very similar to those in Table 3. However, the effect from liquidity on the price difference seems to be less pronounced, indicating that the liquidity advantage of the bookmaker market is smaller for the very popular matches.

5 Conclusion

This paper investigates the coexistence of bookmakers and betting exchanges in the betting industry. Said to exhibit superior odds, less operational risk, lower information costs and higher prediction accuracy, betting exchanges are considered a superior business model to traditional bookmaking. Nevertheless, bookmakers continue to be successful.

We test how liquidity affects the relative price competitiveness of the two market structures. Liquidity in the quote-driven market is continuously provided by the bookmaker. However, liquidity in the order-driven market is determined by limit order submissions from other bettors. We find that the bookmaker offers more favorable

Table 4: Fixed effects panel analysis of price differences (top 10 leagues)

	Dependent variable: Δp					
	Home win		Draw		Away win	
	(1)	(2)	(3)	(4)	(5)	(6)
$QSPR$	-0.497***		-0.499***		-0.665***	
	(0.039)		(0.037)		(0.041)	
$LnVOL$		0.004***		0.003***		0.005***
		(0.0006)		(0.0004)		(0.0006)
Hourly dummies	Yes	Yes	Yes	Yes	Yes	Yes
$F(56, 17{,}672)$	24.87***	6.69***	22.98***	10.70***	28.08***	7.02***
R^2 overall	34.48%	0.57%	43.75%	2.16%	51.45%	0.59%
N	181,084	181,084	181,084	181,084	181,084	181,084
N of groups	1,441	1,441	1,441	1,441	1,441	1,441

Notes: The table reports the coefficients estimated from a fixed effects panel model with standard errors corrected for heteroskedasticity and autocorrelation. Standard errors are reported in parentheses. The dependent variable is the price difference Δp between the two market structures. Only matches from the top 10 leagues worldwide are included in the estimation. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

prices than the betting exchange until 6 hours before match start for *home win* bets and until 3.5 hours before match start for *away win* bets, and less favorable prices thereafter. These price dynamics in the earlier betting period have been overlooked by the literature so far.

A panel regression analysis demonstrates that the price competitiveness of the betting exchange depends crucially on liquidity. Our results imply that a lack of liquidity at the betting exchange causes large gaps between bid and ask prices and thus less competitive betting exchange prices. In such situations, bookmaker prices are superior because liquidity is permanently supplied by the bookmaker.

Altogether, our paper shows that the order-driven betting exchange structure is not necessarily superior to the quote-driven bookmaker structure, as the active management of the sportsbook offers a distinct liquidity advantage. This finding helps to explain the ongoing coexistence of the two structures, as early betting volume should migrate to the more competitive bookmaker market.

Our analysis sheds some light on the recent shift of financial markets into hybrid structures. The London Stock Exchange (LSE) and the Nasdaq market for example, moved from quote-driven systems to a hybrid structure where the order book is supplemented by market makers (Friederich & Payne, 2007). Furthermore, the New York Stock Exchange (NYSE) is characterized by elements of both market structures (Madhavan, 2000). Empirical financial studies suggest that market makers are particularly valuable in hybrid structures when liquidity at the order book is low (e.g., Madhavan & Sofianos, 1998; Friederich & Payne, 2007; Venkataraman & Waisburd, 2007). As such, the hybrid market structure combines the advantages of both the quote-driven and order-driven structures. This might be one of the reasons why *Betfair* has started a sportsbook offering quoted fixed odds in addition to the exchange based odds as of February 2013 (Betfair, 2013a), moving essentially to a hybrid market structure.

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A.3
Does Bettor Sentiment affect Bookmaker Pricing?*

Abstract

This paper uses bookmaker betting volume data to test the influence of bettor sentiment on bookmaker pricing in the *over/under 2.5 goals* betting market. In an average match, more than 80% of the volume wagered is concentrated on the *over* bet as cheering for a high score is more attractive than betting against it. We do not find that this volume imbalance is associated with systematic biases in bettor returns. High price transparency seems to prevent bookmakers from systematically distorting their odds in order to exploit bettor sentiment.

JEL Classification: D81, L83

Keywords: Sports Betting, Sentiment, Bookmaker Odds, Betting Volume

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1 Introduction

Sports betting is a multi-billion dollar business. FIFA (2011) estimates that sports betting generated between $350 billion and $400 billion in 2011 while the sports industry itself generated around $300 billion. The dominant form of sports betting is bookmaker betting. Bookmakers act as dealers by announcing the odds or point spreads that reflect the prices against which bettors can place their bets. Thereby, bookmakers enter the opposite position of each bet. As long as bettor preferences and perceptions are unbiased, bookmakers do best by setting informationally efficient odds that reflect the true winning probability of the underlying event. Otherwise, bookmakers can sustain large losses if bettors are able to recognize and exploit the biased odds (Levitt, 2004). In the presence of sentimental bettors who prefer bets with particular characteristics and who do not necessarily choose the bets with the highest expected return, optimal bookmaker pricing becomes more complex.

Popular examples of bettor sentiment include the optimistic/perception bias (e.g., Kuypers, 2000; Levitt, 2004; Page, 2009) which causes bettors to overrate the winning probability of certain teams, and the loyalty bias (e.g., Forrest & Simmons, 2008; Franck, Verbeek, & Nüesch, 2011) which prevents bettors from betting against the team they support. Bettor sentiment leads to an asymmetric volume demand even when the bookmaker odds reflect the true winning probability of the underlying event.

This paper tests whether and how bettor sentiment affects the pricing strategy of bookmakers. Bookmakers can react to bettor sentiment and thus asymmetric volume demand in three different ways: They can either lengthen or shorten the odds of the more heavily demanded bet or they can refrain from price adjustments and set unbiased odds that provide equal betting returns for all outcomes of the underlying event. Kuypers (2000) and Levitt (2004) argue that bookmakers can maximize their profits by shortening the odds of the bet with the comparatively higher betting volume. Alternatively, the model of Franck et al. (2011) shows that, given a highly elastic demand, risk-neutral bookmakers could profit from lengthening the odds of the more heavily demanded bet. The reasoning behind this pricing strategy is that the lower but still positive margin on such bets is overcompensated by a vast additional betting volume from price-sensitive bettors.

Empirical evidence on the effect of bettor sentiment on bookmaker odds is mixed. Avery and Chevalier (1999), Levitt (2004), Paul and Weinbach (2007) and L. Woodland and Woodland (1994) show that the bettor returns are abnormally low for bets with higher bettor sentiment. Forrest and Simmons (2008) and Franck et al. (2011), however, find higher returns for bets with high bettor sentiment. And while Braun and Kvasnicka (2013) find both upward and downward biases, Page (2009) does not find any evidence of biased odds due to bettor sentiment. Hence, the cumulative evidence on the effect of bettor sentiment on bookmaker pricing is weak and/or inconsistent.

One difficulty in establishing a link between bettor sentiment and bookmaker pricing is that actual betting volume data is often missing. To the best of our knowledge, we are the first to use actual bookmaker betting volume data to analyze the effect of bettor sentiment on bookmaker pricing. Paul and Weinbach (2007, 2009) use data on the percentage of betting volume from Sportsbook.com for the 2007 NFL and NCAA season, while other studies by Paul and Weinbach (e.g., 2008, 2012) use data on the relative number of bets placed from four online sportsbooks (BetUS.com, CribSports.com, SportBet.com and Sportsbook.com) provided by Sportsinsights.com. However, these studies mainly test whether bookmakers attempt to balance their books in the point spread market. Furthermore, the relative number of bets placed is an imprecise measure of betting volume because it ignores the size of the wagers. We use data on the actual percentage of betting volume of a large European bookmaker. The previous sentimental preferences literature typically has only employed proxy measures for sentimental betting demand such as the advice of experts, the historical success or prestige of teams (Avery & Chevalier, 1999), the difference in mean home attendance between the two opposing teams (Forrest & Simmons, 2008; Franck et al., 2011) or the number of bets placed in a betting tournament with a fixed entry fee (Levitt, 2004).

A second difficulty in establishing a link between bettor sentiment and bookmaker pricing is that bettor sentiment is often correlated with other confounders such as bettor risk or skewness preferences (Golec & Tamarkin, 1998; Quandt, 1986) and bookmaker price adjustments due to the risk of the underlying event (Shin, 1991). Thus, empirical patterns in betting markets such as the favorite-longshot bias, which refers to the finding that the expected return of bets with a high winning probability tends to be systematically higher than the return of bets with a low winning probability (see Sorensen & Ottaviani, 2008 for a survey) cannot be attributed solely to bettor sentiment.

We investigate betting returns and volume percentages of the popular *over/under 2.5 goals* betting market on soccer matches.[10] This market is beneficial for three reasons. First, there are only two possible outcomes. An *under 2.5 goals* (hereafter *under*) bet wins if the total score of the two teams is 2 or less and vice versa for the *over 2.5 goals* (hereafter *over*) bet. Second, the average score of a soccer match lies somewhere between 2.4 and 2.6 goals, depending on the league and competition

[10]The *over/under 2.5 goals* betting market is the second largest market after the *winner* market on *home win*, *draw* or *away win* according to the *Betfair* volume data on soccer matches from the 2011/12 season of the *English Premier League* provided by *fracsoft.com*.

(Norman, 2011). Thus, the empirical probability of winning is close to 50% for both the *over* bet and the *under* bet, which indicates that potential risk considerations of bettors and bookmakers are negligible. Third, the *over/under 2.5 goals* betting market allows us to exploit a natural source of sentimental betting. Matches with a high number of total goals are generally more attractive than matches with few or no goals (Paul & Weinbach, 2002; B. Woodland & Woodland, 2010). As gambling is a consumption good, some bettors may even be willing to sacrifice expected returns for the inherent entertainment value of the bet (Conlisk, 1993). Cheering for an exciting high-scoring match is more attractive than cheering for a dull low-scoring match and the entertainment value is therefore certainly higher for the *over 2.5 goals* bet than for the *under 2.5 goals* bet. Hence, at least part of the betting volume wagered on the *over* bet is expected to be sentimentally driven due to this preference. All in all, our setting allows a clean and simple analysis of whether and how bettor sentiment affects bookmaker pricing.

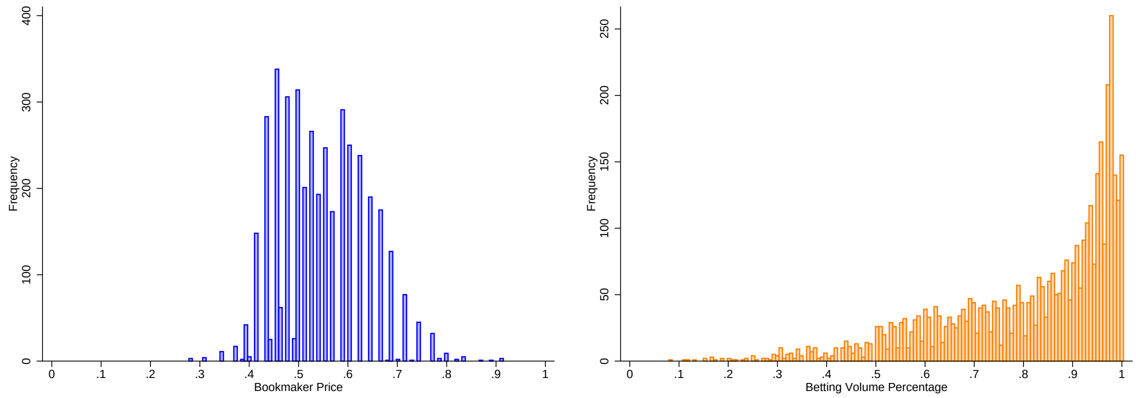
2 Data and Method

We utilize data on the volume percentages of money wagered on each side of the *over/under 2.5 goals* betting market. The betting volume data was provided by the bookmaker *Tipico*, which is one of the leading sports betting vendors in Germany. In addition to the online betting portal, *Tipico* has over 1,000 betting shops in several European countries. The original data sample included 4,491 soccer matches played worldwide in 220 different leagues and competitions between 1 November and 7 December 2011. The corresponding odds information was collected from the website *oddsportal.com*. 372 observations were deleted because bookmaker odds could not be matched.[11] Therefore, the final sample consists of 4,119 matches.

The website *oddsportal.com* publishes both opening and closing decimal odds offered by *Tipico* and up to 62 other bookmakers. The opening odds are the first odds published by a bookmaker, usually one to two weeks in advance, whereas the closing odds are the last odds offered before the match starts. For the empirical analysis we use the closing decimal odds. However, the main results would not change in any significant way if we used the opening odds. For about 60% of all bets, the closing odds are the same as the opening odds.

Decimal odds denote the payoff of a successful bet. For example, if the odds for an *over* bet are 2.50, a one dollar wager pays $2.50 if the total score is 3 or more. We converted the decimal odds into prices, which are the reciprocal of the decimal odds (e.g., $p = 1/2.50 = 0.40$). These prices indicate how much a bettor has to invest in order to collect $1 in the event of a successful bet (Forrest & Simmons, 2008). Figure 1a shows the distribution of the prices from *over* bets offered by the bookmaker *Tipico*. The mean price is 0.54 and the prices appear to be fairly symmetrically distributed around the mean. Figure 1b presents the corresponding distribution of the betting volume percentages wagered on the *over* bet. This distribution is highly asymmetric, with a mean of 0.82 and a skewness of -1.11. Thus, on average, about 80% of the betting volume is concentrated on the *over* bet, leaving 20% of the betting volume for the *under* bet. To test whether the bookmaker prices displayed in Figure 1a exhibit a systematic bias due to the highly asymmetric volume distribution, we conduct simple t-tests for differences in mean objective winning probabilities, betting

[11]The betting volume does not significantly differ between matches with and without missing odds information.



(a) Bookmaker price (b) Betting volume percentage

Figure 1: Distribution of bookmaker prices and betting volume percentages from *over* bets

volume percentages, prices, and bettor returns on a one unit wager between *over* and *under* bets.

To more specifically relate the bettor returns to sentimental betting volume, we estimate a two-stage least-squares (2SLS) model. We use the *over* bet as an identifying instrumental indicator variable to predict the betting volume in the first stage. The first stage regression is specified as

$$volume_{ij} = \theta_0 + \theta_1 \cdot over_{ij} + v_{ij} \tag{1}$$

where $volume_{ij}$ labels the betting volume percentage and $over_{ij}$ refers to an indicator variable equaling 1 for the *over* bet and 0 otherwise for each match i and betting contract type $j \in \{over, under\}$. For each match i, we randomly select either the *over* or the *under* bet to ensure independence across observations. The $over_{ij}$ is a valid instrument because it is highly correlated with the betting volume due to a general human preference for a high score. Additionally, the bettor sentiment on the *over* bets is unrelated to potential confounders such as the winning probability of the favorite team in a match. Hence, our instrument is unlikely to be correlated with the error term of the second stage regression. The second stage is specified as

$$return_{ij} = \beta_0 + \beta_1 \cdot \widehat{volume}_{ij} + \epsilon_{ij} \tag{2}$$

where $return_{ij}$ denotes the bettor's return on a one unit wager calculated from the closing price offered by the bookmaker and $\widehat{volume}_{ij}$ refers to the predicted betting volume according to the first stage regression.

3 Results

Table 1 shows the results from two-sided t-tests for the differences in mean objective winning probabilities (*winning*), betting volume percentages (*volume*), prices (*price*) and bettor returns (*return*) between *over* and *under* bets. The average objective

Table 1: t-tests for differences in mean winning probabilities, volume, prices and returns

	winning		*volume*		*price*		*return*		
	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Std. Dev.
over	0.498	0.008	0.817	0.003	0.544	0.001	-0.086	0.015	0.942
under	0.502	0.008	0.183	0.003	0.539	0.001	-0.068	0.015	0.959
Δ	-0.005	0.156	0.633***	0.005	0.005	0.003	-0.018	0.029	

Notes: The table presents the results from a simple two-sided t-test for the difference in mean objective winning probabilities (*winning*), betting volume percentages (*volume*), prices (*price*) and returns (*return*) between *over* and *under* bets. Additionally, the last column on the right hand side displays the standard deviations of the returns. The number of observations for each test is 4,119. *, **, and *** denote significance at the 5%, 1% and 0.1% levels, respectively.

probability for the *over* bet to win is 49.8% which is not significantly different from the average probability of 50.2% for the *under* bet to win. By contrast, the betting volume is highly concentrated on the *over* bet, accounting for 81.7% of the betting volume on average. However, this highly asymmetric betting volume does not seem to affect bookmaker pricing and bettor returns. The t-tests show that the differences in the mean prices and mean returns are not statistically different between the *over* bet and the *under* bet.[12] Non-parametric Wilcoxon sign-rank tests confirm these findings. Risk considerations of bettors or bookmakers should not affect these results because the objective probability of the *over* and the *under* bet to win is close to 50% (see first column of Table 1) and the standard deviations of the returns are very similar (see last column of Table 1).[13]

The results from the 2SLS model are shown in Table 2. Column (1) reports the estimates of the first stage regression, which predicts the betting volume. Our instrument *over* is a strong predictor for the volume with a partial R^2 of around 88%. Column

Table 2: 2SLS regressions of returns

	First stage: *volume*	Second stage: *return*
	(1)	(2)
$\widehat{volume}$		-0.038
		(0.047)
over	0.633***	
	(0.005)	
Partial R^2 / R^2	87.81%	0.67%
N	4,119	4,119
Kleibergen-Paap rk LM statistic		3,166***

Notes: The table presents 2SLS estimates for closing prices and bettor returns. The betting volume is instrumented by the *over* indicator variable. For each match, only one bet (either *over* or *under*) is randomly included. The heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 5%, 1% and 0.1% levels, respectively.

(2) reports the estimates of the second stage regression on the relation between the

[12] This result is robust to the use of returns calculated from opening prices of *Tipico* and returns calculated from prices offered by up to 62 different bookmakers including *Bwin*, *Ladbrokes* and *William Hill*.

[13] The results of a variance ratio test show that the standard deviations of the returns from *over* and *under* bets are not statistically different.

predicted betting volume and bettor returns. The sentimental betting volume does not significantly affect the returns. Thus, high sentimental betting volume does not cause abnormally high or low bettor returns.[14]

4 Conclusion

We use actual betting volume data to analyze the effect of bettor sentiment on bookmaker pricing in the *over/under 2.5 goals* betting market of soccer matches. This market offers ideal conditions because bettors exhibit a natural preference for high match scores. At the same time, the empirical winning probability for either bet to win is close to 50%, indicating that potential risk considerations of bettors and bookmakers that could interfere our results are negligible in this setting.

We find that the betting volume from the *over/under* market is highly concentrated on the *over* bet, accounting for over 80% of the betting volume on average. However, this imbalance is not associated with systematic sentimental biases in bookmaker pricing and bettor returns.

Our results do not necessarily imply that bookmaker prices are always unbiased. If the sentimental betting volume is positively correlated with the objective winning probability of the underlying bet, bookmakers' prices may still be biased. Forrest and Simmons (2008) and Franck et al. (2011) find that bookmakers offer significantly more favorable prices for bets on wins by strong teams with a large supporter base.

This paper shows that in a setting where risk considerations of both bettors and bookmakers are negligible, bookmakers do not distort their prices to exploit the bettor preference to bet on a high number of goals in a soccer match. Instead, bookmakers

[14] Again, this finding is robust to the use of returns based on opening prices and returns based on average bookmaker prices calculated from prices offered by up to 62 different bookmakers.

offer prices that reflect their best prediction of the true outcome probability and add an equally distributed commission, even when bettor sentiment leads to a highly asymmetric volume distribution.

One possible explanation for this finding is that bettors can easily compare the prices listed by several different bookmakers and find the best prices through a number of websites such as *oddsportal.com* or *betbrain.com*, which increases the bettors' price sensitivity. Thus, small price changes tend to have a large impact on the betting volume and eventually on the bookmaker's profit. If a bookmaker increases the price (shortens the odds) of an *over* bet, sentimental bettors would switch to a competitor. On the other hand, if a bookmaker lowers the price (lengthens the odds) of an *over* bet, he gains additional sentimental betting volume, however, at a higher risk of substantial losses.

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A.4
Liquidity, Market Efficiency and the Influence of Noise Traders: Quasi-Experimental Evidence from the Betting Industry*

Abstract

This paper examines how liquidity affects market efficiency in a market environment where securities' true values are revealed at a predetermined point in time. We employ differences in minimum tick sizes at the betting exchange *Betfair* which induce exogenous variation in liquidity. The results show that liquidity significantly decreases market efficiency for bets on weekend matches but not for bets on weekday matches. As uninformed noise bettors are more likely to bet on weekends than on weekdays, the type of liquidity seems to matter for market efficiency.

JEL Classification: G12, G14

Keywords: Liquidity, Market Efficiency, Noise Trading, Betting Market

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*This paper has been written jointly with Stephan Nüesch and Egon Franck.

1 Introduction

To provide an optimal allocation of capital, financial markets have to be informationally efficient, so that prices of securities fully reflect all information available (Fama, 1991). This paper tests how liquidity affects informational market efficiency. The relation between liquidity and efficiency is controversial. On the one hand, liquidity lowers transaction costs and the impact of individual orders on prices (O'Hara, 1995). Thus, arbitrageurs have more incentive to acquire information and trade more aggressively on this information, which should force the prices to drift closer to their fundamental values (Kyle, 1985). Several empirical studies show that increasing liquidity results in enhanced market efficiency (e.g., Chordia, Roll, & Subrahmanyam, 2008; Chung & Hrazdil, 2010a; Sadka & Scherbina, 2007; Wurgler & Zhuravskaya, 2002). On the other hand, high liquidity due to irrational noise traders could prevent arbitrageurs from trading sufficiently against them and result in a higher mispricing relative to the prices in illiquid markets (Shleifer & Vishny, 1997; De Long, Shleifer, Summers, & Waldmann, 1990). Bloomfield, OHara, and Saar (2009) and Linnainmaa (2010) provide empirical evidence of greater mispricings in liquid markets.

Empirical financial studies face two major limitations when investigating the relation between liquidity and market efficiency. First, fundamental values of traditional financial products are not observable. Therefore, all field studies must test market efficiency jointly with an equilibrium model (Fama, 1970). Second, the amount of liquidity is an endogenous function of the pricing accuracy. In models of adverse selection, for example, a release of information about a security's fundamental values, i.e., an improvement in market efficiency, is associated with preceding periods of illiquidity because limit order submitters worry that other traders who submit market orders possess superior information (Tetlock, 2008).

We use data from a major betting exchange to investigate the relation between liquidity and market efficiency. As in order-driven financial markets, betting exchanges facilitate a continuous double auction process. However, betting exchanges differ from financial markets in their informational environment. Betting contracts have a clear endpoint at which their fundamental value is revealed. Furthermore, the underlying outcome of such contracts, e.g., the home team to win a match, is affected neither by the trader's expectations nor by macroeconomic factors. By contrast, traditional financial securities are infinitely lived and have, unless the underlying firm goes bankrupt, no point in time where the true fundamental value is revealed. Thus, betting markets offer a unique setting for measuring the informational market efficiency of prices (Sauer, 1998; Verbeek, 2011).

So far, few studies link the market efficiency of betting markets to liquidity. Tetlock (2008) employs data of financial and sporting contracts from the *TradeSports* exchange. He concludes that higher liquidity increases mispricing and that prices of illiquid securities converge more quickly towards their fundamental value. To overcome the reverse causality problem between liquidity and efficiency, Tetlock (2008) employs the exchange-wide trading activities as instrumental variables for changes in liquidity. However, because aggregated liquidity might be related to aggregated mispricing within the exchange, these instrumental variables may not be truly exogenous. Croxson and Reade (2011) use high-frequency in-play betting data on soccer matches from a betting exchange and do not find any significant relationship between liquidity and market efficiency. They do not address the endogeneity of liquidity.

To estimate the causal effect of liquidity on market efficiency we employ differences in minimum tick sizes that create exogenous variation in liquidity at the betting exchange *Betfair*. In combination with the observation of the fundamental value of the contracts traded at the betting exchange, this exogenous variation means that *Betfair* offers a quasi-experiment to investigate the influence of liquidity on market efficiency.

We use betting contracts on 2,227 soccer matches played in the *English Premier League* from 2006-2011 and in the *Spanish Primera Divisón* from 2009-2011 traded at the betting exchange *Betfair*. Using different liquidity and efficiency measures, the results from our two-stage least squares model (2SLS) estimation show that market efficiency is negatively associated with liquidity.

Earlier studies (Kopelman & Minkin, 1991; Sobel & Raines, 2003; Sung & Johnson, 2007) have shown that the betting activity at weekend matches is characterized by a higher share of irrational noise bettors than betting activity at weekday matches. We find that the negative effect of liquidity is more pronounced for weekend matches whereas the effect becomes insignificant for weekday matches.

Overall, our findings indicate that liquidity with a high fraction of noise bettors decreases market efficiency, whereas liquidity with a low fraction of noise bettors is not significantly related to market efficiency. A high fraction of noise bettors prevents prices from adjusting to their fundamental values. One reason for the persistence of mispricing is bettor sentiment, which causes noise bettors to prefer bets with particular characteristics. Similar to investor sentiment in financial markets (e.g. Barberis, Shleifer, & Vishny, 1998; Baker & Wurgler, 2006; De Long et al., 1990), bettor sentiment is found to bias prices in betting markets due to incorrect perceptions (e.g., Kuypers, 2000; Levitt, 2004) or loyalty towards certain teams (e.g., Forrest & Simmons, 2008; Franck, Verbeek, & Nüesch, 2011).

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes our data and discusses how we process our empirical analysis. Section 4 reports the main estimation results and Section 5 concludes.

2 Literature Review

The relation between liquidity and market efficiency has important implications for policy makers and regulators. From a theoretical perspective, two competing hypotheses have evolved. On one side, liquidity facilitates the elimination of mispricings and thus increases market efficiency due to lower transaction costs (O'Hara, 1995). On the other side, liquidity due to uninformed or irrational noise trading decreases market efficiency because rational agents are unable to fully offset noise traders' biases (De Long et al., 1990). Earlier studies within the market microstructure literature have also addressed the link between liquidity and market efficiency. However, the findings are widely inconsistent.

Several studies support the view that prices of securities in liquid markets exhibit higher market efficiency. The theoretical model proposed by Kyle (1985) shows that with increasing liquidity informed traders are able to trade more heavily on their information without impacting the prices. As such, liquidity providers camouflage the trading from informed traders which allows them to increase their profits. Therefore, liquid markets reduce the transaction costs for arbitrageurs and encourage them to acquire information in those markets to correct mispricings.

Wurgler and Zhuravskaya (2002) provide indirect empirical evidence and test how prices respond to exogenous demand shocks of stocks that were added to the S&P 500 Index. The authors find that stocks without close substitutes, which thus present a higher arbitrage risk, exhibit a steeper demand curve and higher mispricing. As steeper demand curves imply less liquidity, mispricing is greater in illiquid markets due to risk averse arbitrageurs who will trade less aggressively when arbitrage risk is high.

Sadka and Scherbina (2007) provide further evidence for a positive link between liquidity and market efficiency. They investigate stocks with high analyst disagreement. As the information about the earnings becomes publicly available at a certain point in time, mispricing of such stocks tends to be short-lived. Sadka and Scherbina (2007) find that less liquid stocks tend to be more severely overpriced due to higher trading costs. In an additional time series analysis, the authors show that increasing aggregated liquidity accelerates the convergence of prices to fundamentals.

The study of Chordia et al. (2008) is one of the first to analyze the short horizon return predictability in connection with liquidity. The authors examine the five-minute return predictability from lagged order flow of 193 NYSE firms as an inverse measure of market efficiency. Between 1993 and 2003, the minimum tick size in bid-ask spreads decreased, providing an exogenous increase in liquidity. Because return predictability declined across the three tick size regimes, liquidity is found to be positively related to market efficiency. Chordia et al. (2008) conclude that higher liquidity facilitates efficiency via two distinct channels. First, arbitrageurs better absorb the asymmetric order flow in periods of high liquidity, which speeds up the convergence of prices to fundamental values. Second, the reduced minimum price change enables the correction of smaller mispricings.

Chung and Hrazdil (2010a) apply the methodology of Chordia et al. (2008) to a comprehensive sample of 4,222 NYSE firms between 1993 and 2004. Using the inverse adjusted R^2 from the estimation results of the short horizon return prediction as a proxy for market efficiency, the authors find that liquidity measured as the inverse effective bid-ask spread is positively related to market efficiency. This positive relation is amplified during periods of newly disclosed information. The findings of Chung and Hrazdil (2010a) are robust to potential confounding effects emerging from the trading frequency and the firm size. A further study by Chung and Hrazdil (2010b) investigates the return predictability of 11,073 NASDAQ firms across three minimum tick size regimes. As before, they observe that liquidity increases market efficiency.

One major concern of using the return predictability as an inverse indicator of market efficiency is that large deviations from fundamental values could be present without leaving statistically identifiable traces in the pattern of ex-post returns (Summers, 1986). Additionally, Chordia et al. (2008) and Chung and Hrazdil (2010a, 2010b) analyze the relation between liquidity and market efficiency during a time period in which large technical advances were made and access to information became less costly. Hence, contemporaneous confounders are very difficult to rule out.

Other studies support the view that prices of securities in liquid markets exhibit lower market efficiency. De Long et al. (1990) argue that noise traders' beliefs could deviate from the asset's fundamental value over long periods of time. These beliefs affect prices and lead to a loss for the arbitrageur if she has to liquidate her position before the price recovers. The fear of loss hinders the arbitrageur from entering a position and trading aggressively against noise traders in the first place. As a result, arbitrageurs start to predict the pseudosignals from noise traders such as volume and price patterns or sentiment indices rather than trading on fundamentals to correct mispricings.

Moreover, the model of Shleifer and Vishny (1997) challenges the view that a large number of tiny arbitragers with small stakes are the ones taking position against mispricings. In fact, the small traders are typically not the ones who are informed. Rather, arbitrage is conducted by a relatively small number of professionals who take large positions with funds from outside investors. When prices diverge far from fundamental values due to noise traders, arbitrageurs with their own funds would generally increase their positions. However, arbitrageurs who manage other people's money have to fear an early liquidation of the positions due to their investors' pressure. Hence, arbitrageurs tend to avoid such volatile positions, which makes them less effective in achieving market efficiency.

One explanation of the persistence of mispricing over longer periods of time is investor sentiment that results from psychological misperceptions in making forecasts. For example, Barberis et al. (1998) predict in their theoretical model that investors underreact to earnings announcements and similar events, and overreact to consistent patterns of good or bad news.

In an experimental market study, Bloomfield et al. (2009) examine how uninformed noise trading affects market efficiency. As expected, such traders increase the market liquidity dramatically. However, the presence of uniformed noise traders also harms market efficiency because their unwise contrarian strategies prevent market prices from adjusting to new information.

A similar conclusion can be drawn from Linnainmaa (2010) who investigates limit orders using a detailed dataset of investor trading records. In his data set from Finland, 76.3% of individuals' orders are limit orders. One reason for individual traders to use limit orders is the potential gain from the liquidity demand of impatient investors who place market orders. However, their limit orders only execute if the price moves against the order, for example around positive earnings announcements.

As a result, such individual and uninformed traders can be interpreted as liquidity providers who harm the process of adjustment to the intrinsic value.

Studies that investigate the link of liquidity and market efficiency in prediction and/or betting markets are scarce. Tetlock (2008) investigates contracts on binary financial and sporting event outcomes from the *TradeSports* exchange, where the fundamental values of the contracts are revealed at a predetermined point in time. To overcome the reverse causality problem between liquidity and efficiency, Tetlock (2008) constructs instrumental variables based on the exchange-wide liquidity. However, if aggregated liquidity is related to aggregated mispricing, those instruments may not fully resolve the endogeneity problem. One likely scenario would be that the aggregated liquidity at the weekend is widely influenced by casual bettors who might also affect the market efficiency. The results of Tetlock (2008) indicate that liquidity increases the deviation of prices from the fundamental value of the contracts and thus harms market efficiency. Similar to Linnainmaa (2010), he explains this finding by naive and passive limit order traders who bet against market order traders in informative periods and thus decelerate the response of prices to information.

Hartzmark and Solomon (2012) provide further evidence for the negative effect of liquidity on market efficiency in betting markets. They examine NFL betting contracts from the *TradeSports* exchange and find that the more liquid Monday Night games exhibit greater mispricings than other games.

Croxson and Reade (2011) use high-frequency soccer betting market data from the betting exchange *Betfair*. Although the main focus lies on a general assessment of the market efficiency at the betting exchange, Croxson and Reade (2011) investigate whether liquidity affects mispricings. Using the squared difference between the efficient price drift estimated by a Poisson model and the actual price drift as efficiency measure, the authors are unable to find any effect of liquidity on mispricings and conclude that the price drift is efficient. However, the study of Croxson and Reade (2011) does not address the potential simultaneity of liquidity and market efficiency.

Overall, previous findings are inconsistent with regard to the general effect of liquidity on market efficiency. However, there is wide consensus that *noise trader liquidity* decreases market efficiency.

Kopelman and Minkin (1991) state that weekend bettors at the racetrack are more casual and choose their bets based on irrelevant factors such as the name or color of the horses, whereas weekday bettors are highly knowledgeable about their pursuits and motivated by the desire for financial gain. Moreover, Sobel and Raines (2003) find that weekend bettors wager a significantly lower amount per person and are less informed. Finally, Sung and Johnson (2007) provide evidence that prices for weekend markets exhibit lower market efficiency than weekday markets because weekend markets are populated by a larger proportion of noise bettors.

This paper is the first to investigate the relation between liquidity and market efficiency in a setting where exogenous variation in liquidity is created by different minimum tick sizes and the fundamental values of securities are revealed at a predetermined point in time. By investigating the effect of liquidity on market efficiency for weekend and weekday matches separately, we are able to test the hypothesis that noise trader liquidity decreases market efficiency.

3 Data and Methods

3.1 Sample

We use betting data on professional soccer matches from the popular *winner* betting contracts on *home win*, *draw* or *away win* traded at *Betfair*, the most prominent betting exchange worldwide. *Betfair* provides an electronic platform on which bettors can directly trade bets with each other in a continuous double auction. Thus, as in the order-driven system of financial markets, individual bettors can post limit and/or market orders under which they are willing to place a bet on (buy order) or against (sell order) a given outcome of a match. The latent demand and supply in the form of limit orders is collected and displayed in the order book with a bid-ask spread between the best buying and selling orders. A transaction takes place whenever two parties agree on one price (Verbeek, 2011). This new form of sports betting has grown rapidly in the last years. Its economic relevance is now considerable and in some cases comparable to common financial markets. *Betfair* had over 4 million registered customers and processed more than 7 million transactions on an average day in 2012 (Betfair, 2012b). The NYSE Group processed about 5.5 million trades on an average trading day in 2012 (NYSE, 2012).

Our sample consists of decimal betting odds information on 2,227 matches played in the *English Premier League* from 2006/07-2011/12 and in the *Spanish Primera Divisón* from 2010/11-2011/12. The dataset covers the last three hours before match start and is provided by *Fracsoft*, a vendor of historical *Betfair* data.[15] Decimal

[15] The completeness of the data increased continuously over time. The percentages of missing matches are 64% (Season 06/07), 52% (07/08), 20% (08/09), 13% (09/10), 13% (10/11) 12% (11/12) for the *English Premier League* and 21% (10/11), 19% (11/12) for the *Spanish Primera Divisón*. Because matches are missing due to technical reasons (Choi & Hui, 2012), sample selection should not affect our results.

betting odds denote the payoff of a successful bet. For example, if the odds for an *home win* bet are 1.60, a one dollar wager pays $1.60 if the home team wins the match.

For each event within a match, i.e., *home win*, *draw* and *away win*, we have second-by-second information on the best back odds, which are the best odds offered to buy a bet, the best lay odds, which are the best odds to sell a bet, and the last odds to have been matched. For the ease of interpretation we convert the decimal odds into prices, defined as the reciprocal of the decimal odds (e.g., $p = \frac{1}{1.60} = 0.625$), ranging from zero to one. These prices indicate how much a bettor has to invest in order to collect $1 in the event of a successful bet (Forrest & Simmons, 2008). Additionally, our dataset contains the current limit order volume available on both back and lay bets and the cumulative trading volume until time t before match start.

3.2 Liquidity Measures

The most commonly used measures of liquidity in the financial market microstructure literature are spread-related (e.g., Amihud & Mendelson, 1986; Chordia, Roll, & Subrahmanyam, 2001; Hasbrouck & Seppi, 2001; Lin, Snager, & Booth, 1995). The spread approximates the costs incurring with trading. Thus, small spreads indicate high liquidity in the market (Von Wyss, 2004). We follow the approach of Chordia et al. (2008) and use the quoted spread, defined as the difference between the lowest ask price and the highest bid price, as an inverse measure of liquidity. For each match i, event $e \in \{$*home win*, *draw*, *away win*$\}$ and time t before match start, we calculated the quoted spread ($QSPR$) as

$$QSPR_{iet} = p_{iet}^{back} - p_{iet}^{lay} \tag{1}$$

where p^{back} refers to the best ask price and p^{lay} to the best bid price, respectively. The quoted spread is always positive and its lower limit is at the minimum tick size (Von Wyss, 2004).

A unique feature of the *Betfair* trading platform is the increment rule that defines the minimum tick size. Table 1 depicts the odds increments over the possible odds range at *Betfair*. For short odds, e.g., between 1.01 and 1.99, the minimum odds

Table 1: Odds increments at *Betfair*

odds	]1;2[	[2;3[	[3;4[	[4;6[	[6;10[	[10;20[	[20;30[	[30;50[	[50;100[	[100;1000[
odds inc.	0.01	0.02	0.05	0.1	0.2	0.5	1	2	5	10

Notes: The table presents the *acceptable* odds increments at the *Betfair* betting exchange as stated in Betfair (2012a).

increment is 0.01, whereas for long odds, e.g., between 10 and 19, the minimum odds increment increases to 0.5. The increment rule results in a discontinuous and non-linear minimum quoted spread ($MSPR$) function. Figure 1 depicts the minimum quoted spread function defined by *Betfair* and the actual quoted spread from our dataset for all possible midquote prices (p^M) calculated as the average between the best ask price and the best bid price. As expected, the correlation between the quoted spread and the minimum quoted spread seems to be positive, but the minimum quoted spread does not predict the actual quoted spread perfectly. Moreover, there are clear drops in the quoted spreads at midquote price levels of 0.50 and 0.33, for example.

As a second measure of liquidity we use the quote slope which combines both price and quantity information (Hasbrouck & Seppi, 2001). If more volume is available at the best bid or ask price, the quote slope decreases and the market is more liquid. Similarly, if the bid and ask price are closer to each other, the quote slope decreases

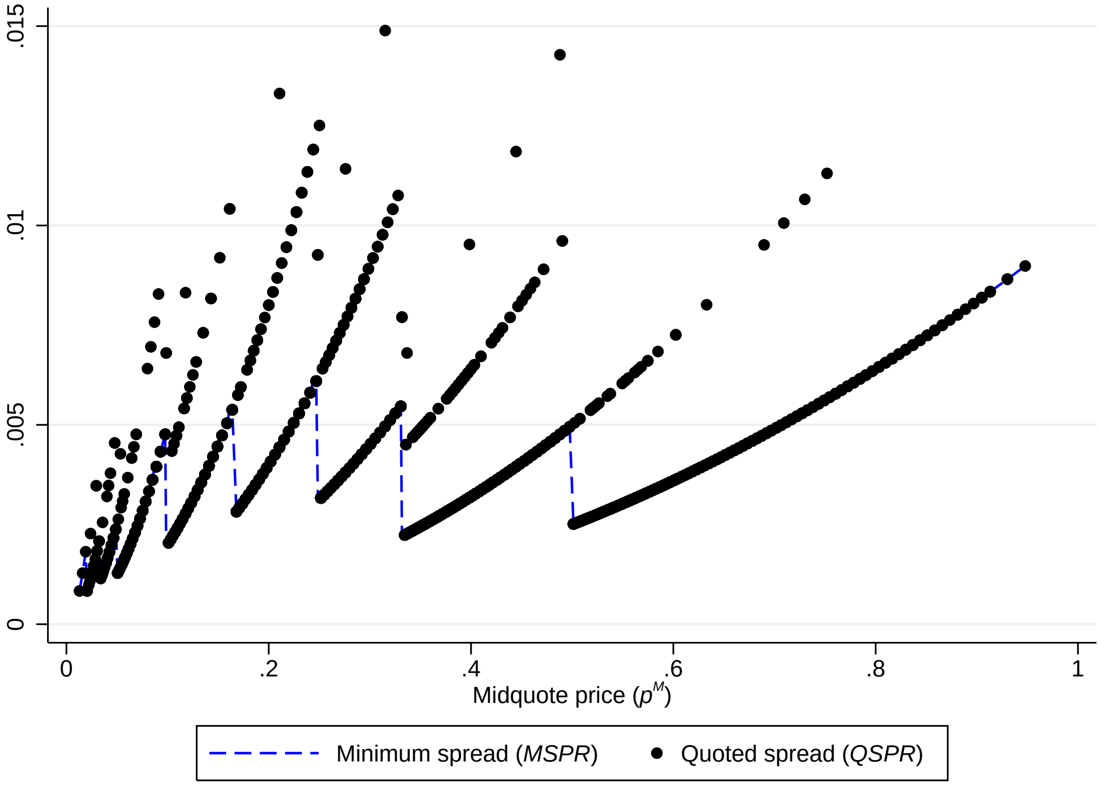


Figure 1: Minimum spread function and quoted spread

and the market is more liquid. Thus, a high quote slope indicates low liquidity. Formally, the quote slope in the betting exchange market is defined as

$$QSLP_{iet} = \frac{p^{back}_{iet} - p^{lay}_{iet}}{ln(vol^{back}_{iet}) + ln(vol^{lay}_{iet})} \tag{2}$$

where vol^{back} and vol^{lay} denote the best back and lay volume available in the limit order book for event e at time t.

Several financial studies such as Chordia et al. (2001), Gervais, Kaniel, and Mingelgrin (2001) and Lee and Swaminathan (2000) incorporate volume-related liquidity measures. Therefore, we use the logarithmized cumulative trading volume from the opening of the market till time t before match start ($LnVOL$) as a third liquidity measure.

Table 2 reports summary statistics associated with our liquidity measures 60 minutes before match start. Because each of the 2,227 matches consists of the three events *home win*, *draw* and *away win* the total number of observations is 6,681. As expected, the average quoted spread is higher than the average minimum quoted spread. The average cumulative volume traded is £248,000.

Table 2: Summary statistics of liquidity measures (60 minutes before match start)

Variable	Description	N	Mean	Std. Dev.	Min	Max
$MSPR$	Minimum quoted spread	6,681	0.0040	0.0010	0.0008	0.0090
$QSPR$	Quoted spread	6,681	0.0042	0.0014	0.0008	0.0149
$QSLP$	Quote slope	6,681	0.0003	0.0001	0.0001	0.0012
$LnVOL$	Log. cum. volume traded	6,681	11.261	1.5003	7.3708	15.541

Notes: The table reports the summary statistics of liquidity measures 60 minutes before match start. The data is obtained from *Fracsoft* and spans the seasons 2006/07-2011/12, including matches from the *English Premier League* and the *Spanish Primera Divisón*. The total number of matches is 2,227, with each match covering the three events *home win*, *draw* and *away win*.

3.3 Market Efficiency Measures

Our measures of market efficiency make use of the advantage that the fundamental value of each betting contract is observed after the match. Because the outcome of a bet is either 1 (win) or 0 (loss) the prices quoted at the betting exchange can be interpreted as the market's forecasting probability of an individual bet to win. Hence, we employ scoring rules that have been developed by the probabilistic forecasts verification literature to provide a summary measure for the efficiency of prices (Gneiting & Raftery, 2007). Scoring rules assess the ex post informativeness of the probabilities after the outcome is known (Jose, Nau, & Winkler, 2009).

The most common scoring rule is the Brier score (Brier, 1950). The Brier score is based on the squared error, defined as the squared difference between individual pairs of forecasts and observations. Because the Brier score captures both the resolution and the calibration of a forecast, it forms an attractive measure of market efficiency (Murphy & Winkler, 1987; Gneiting, Balabdaoui, & Raftery, 2007). The resolution refers to the ability of the forecast probability to discriminate between high- and low-probability events, whereas the calibration refers to the correspondence of the forecast probability and the true observed frequencies (I. Mason, 1982). To also take the difficulty of the forecasting problem into account, the Brier score is widely expressed as a skill score that measures the extent to which a forecast outperforms a reference forecast (S. Mason, 2004; Wilks, 1995). Formally, the Brier skill score (BSS) is defined as

$$BSS_{iet} = 1 - \frac{(Y_{ie} - p_{iet}^{M})^2}{(Y_{ie} - p_{iet}^{ref})^2} \tag{3}$$

where Y refers to the actual outcome, which is either a win (1) or a loss (0), and p^M refers to the quoted midpoint price as the market's valuation for the underlying value of the bet. The numerator of the ratio reflects the Brier score of the actual forecast and the denominator reflects the Brier score of a reference forecast. One of the most widely used reference forecasts is the *climatological probability* of the outcome to occur (Jolliffe & Stephenson, 2003). In our setting, the *climatological probability* is the noninformative price of 0.333 for each of the three events within a match. Thus, the denominator takes on the value 0.444 if the outcome occurs and 0.111 if the outcome does not occur. The BSS ranges from one for a perfect forecast, through zero for a forecast that provides no improvement over the reference, to negative values for forecasts worse than the reference (S. Mason, 2004).

Our second measure of market efficiency is the absolute error skill score ($AESS$) which is more reliable than the Brier skill score in the presence of outliers (Armstrong, 2001). The $AESS$ is based on the ratio of the absolute error of the actual forecast and the absolute error of a reference forecast. We calculate the absolute error skill score as

$$AESS_{iet} = 1 - \frac{\mid Y_{ie} - p_{iet}^{M} \mid}{\mid Y_{ie} - p_{ite}^{ref} \mid} \tag{4}$$

The $AESS$ has a value of one for a perfect accuracy, a value of zero when the forecast contains no skill and a negative value when the accuracy is lower than the uninformed reference forecast of 0.333. Table 3 reports the summary statistics of our market

Table 3: Summary statistics of efficiency measures (60 minutes before match start)

Variable	Description	N	Mean	Std. Dev.	Min	Max
BSS	Brier skill score	6,681	0.1166	0.8724	-6.5064	0.9985
$AESS$	Absolute error skill score	6,681	0.1511	0.4035	-1.7398	0.9613

Notes: The table reports the summary statistics of efficiency measures 60 minutes before a match start. The data is obtained from *Fracsoft* and spans the seasons 2006/07-2011/12, including matches from the *English Premier League* and the *Spanish Primera Divisón*. The total number of matches is 2,227, with each match covering the three events *home win*, *draw* and *away win*.

efficiency measures 60 minutes before match start. The positive means show that betting exchange prices incorporate more information on average than the reference forecast.

3.4 Identification Strategy

Our empirical analysis is divided into three parts. First, we make use of the discontinuity of the minimum quoted spread function displayed in Figure 1 by forming subsamples of observations which are ±0.025 price units around the discontinuity area. This results in two groups with different inherent liquidity but similar prices. One group with observations below the discontinuity is considered as the *high gap MSPR* group. The other group with observations above the discontinuity is considered as the *low gap MSPR* group. We conduct parametric t-tests as well as nonparametric Wilcoxon rank sum tests of the difference in market efficiency between the two liquidity groups.

In a second analysis, we use the predetermined minimum quoted spread function ($MSPR$) of *Betfair* as an identifying instrumental variable for our liquidity measures (L). The first stage equation is

$$L_{ie} = \theta_0 + \theta_1 \cdot MSPR_{ie} + \theta_2 \cdot p_{ie}^M + \theta \cdot \Gamma_{ie} + u_{ie} \tag{5}$$

where p^M refers to the midquote price of the bet and Γ refers to a set of control variables such as dummy variables for the event e, seasons and leagues. As can be seen from Figure 1, the $MSPR$ is an increasing function of p^M, making the midquote price an important control variable (Angrist & Pischke, 2009). The second stage equation is formulated as

$$E_{ie} = \beta_0 + \beta_1 \cdot \widehat{L_{ie}} + \beta_2 \cdot p_{ie}^M + \beta \cdot \Gamma_{ie} + \epsilon_{ie} \tag{6}$$

where E is the measure of market efficiency and $\widehat{L}$ is the fitted value of the first stage regression estimated in Equation (5). The second stage regression has the same set of control variables as the first stage regression. Because we control for the midquote price p^M, the favorite-longshot bias does not distort our results. The favorite-longshot bias refers to the empirical observation that favorite teams are often underpriced and longshots are overpriced (e.g., Snowberg & Wolfers, 2010; Thaler & Ziemba, 1988).

Third, we split our sample into matches played on weekends and on weekdays and estimate Equations (5) and (6) for weekend and weekday matches separately. Based on the findings from the previous literature (Kopelman & Minkin, 1991; Sobel & Raines, 2003; Sung & Johnson, 2007) we expect liquidity on weekends to be more heavily affected by noise traders than liquidity on weekdays. Because all teams in the same league play the same number of weekday matches, this allocation is neither correlated with certain teams nor with their objective winning probability (Franck et al., 2011).

4 Results

Table 4 presents the means of market efficiency of the *low gap MSPR* and the *high gap MSPR* groups as well as the results of t-tests and Wilcoxon rank sum tests on the differences between the groups. While Panel A uses BSS as market efficiency measure, Panel B uses $AESS$ as efficiency measure. Table 4 shows that market efficiency is significantly higher in the *high gap MSPR* group than in the *low gap MSPR* group, independent of the efficiency measures and tests employed.[16]

Table 5 displays the results of the first stage regressions that relate the minimum spread ($MSPR$) to the liquidity measures ($QSPR$, $QSLP$, and $LnVOL$). As expected, we find significantly positive effects of $MSPR$ on our spread-related liquidity measures and a significantly negative effect of $MSPR$ on the logarithm of betting volume. As the F-statistics of our identifying instrument are far beyond the critical threshold value of 8.96 (Stock, Wright, & Yogo, 2002), we do not have a weak in-

[16]This finding is robust to the use of the nonparametric relative operating characteristic curve (ROC) as an alternative measure of market efficiency (see Figure A.1 in Appendix A.1). Moreover, betting prices have significantly lower explanatory power in the *low gap MSPR* group than in the *high gap MSPR* group, which also confirms that liquidity decreases market efficiency (see Table A.1 in Appendix A.1)

Table 4: Liquidity and market efficiency at discontinuity area

Panel A: comparison of BSS

		t-test			Wilcoxon rank sum test		
	N	Mean	SE	t	rank sum	expected	z
Low gap MSPR	1,353	0.3442	0.0151		1,584,839	1,730,487	
High gap MSPR	1,204	0.3887	0.0176		1,685,564	1,539,916	
Δ	2,557	-0.0445	0.0230	-1.932*			-7.817***

Panel B: comparison of $AESS$

		t-test			Wilcoxon rank sum test		
	N	Mean	SE	t	rank sum	expected	z
Low gap MSPR	1,353	0.2652	0.0093		1,584,839	1,730,487	
High gap MSPR	1,204	0.3149	0.0108		1,685,564	1,539,916	
Δ	2,557	-0.0498	0.0145	-3.507***			-7.817***

Notes: The table presents the results of simple two-sided t-tests and Wilcoxon rank sum tests based on the two groups *low gap MSPR* and *high gap MSPR*. The groups are formed from observations located ±0.025 price units around the discontinuity gaps of the $MSPR$ function. Panel A displays the results for the differences in BSS and Panel B displays the results for the differences in $AESS$. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

strument problem. Table 5 also shows that the midquote price p^M positively affects liquidity, which indicates that bettors prefer betting on favorite teams over betting on longshot teams (see also Levitt, 2004). Additionally, matches played in the *English Premier League* are associated with more liquidity than matches played in the *Spanish Primera Divisón*. This is not surprising as sports betting is more popular in England than in Spain.

Table 6 reports the results of the second stage regression. We find positive coefficients of the quoted spread and the quote slope, and negative coefficients of the trading volume on BSS (Columns (1) - (3)) and on $AESS$, respectively (Columns (4) - (6)). Thus, liquidity is negatively related to market efficiency.[17] In all specifications

[17]The results remain virtually the same if we use the effective spread as an alternative spread-related measure. The effective spread is defined as twice the absolute difference of the last transaction

Table 5: First stage results of 2SLS model estimation

	$QSPR$	$QSLP$	$LnVOL$
	(1)	(2)	(3)
$MSPR$	1.019***	0.063***	-93.12***
	(0.022)	(0.002)	(16.41)
p^M	-0.0003***	-0.0002***	5.623***
	(0.0001)	(0.00001)	(0.112)
home	-0.00003	0.00000	0.692***
	(0.0001)	(0.00001)	(0.049)
away	0.00006	0.00002***	0.613***
	(0.0001)	(0.00001)	(0.041)
Primera División	0.0001*	0.00004***	-1.097***
	(0.0001)	(0.00001)	(0.045)
Season Dummies	Yes	Yes	Yes
N	2,227	2,227	2,227
partial R^2	52.68%	30.69%	1.33%
F-test of the excluded instrument	2,172***	806***	32.21***

Notes: The table presents the first stage estimates for the quoted spread ($QSPR$), quote slope ($QSLP$) and the cumulative trading volume ($LnVOL$) from the *Betfair* minimum quoted spread ($MSPR$). The data is taken 60 minutes before the match starts. To ensure independence across observations, we randomly selected one event (*home win*, *draw*, *away win*) per match. Heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

we include the midquote price p^M, event dummies, a league dummy for the *Primera División* and seasonal dummies as control variables.[18]

We run the regressions separately for each minute during the last three hours before match start. The resulting coefficient estimates for the quoted spread on the Brier skill score and on the absolute error skill score are displayed in Figure A.2 of Appendix A.2. The estimated coefficients are positive and remain relatively stable

price and the prevailing midquote price between the best bid and ask price (Bessembinder, 2003). Moreover, our results do not change if we use the absolute pricing error to measure market inefficiency employed by other studies such as Bloomfield et al. (2009), Wolfers and Zitzewitz (2004) or Snowberg and Wolfers (2010).

[18] The results are also robust to the inclusion of team dummies. Thus, time-constant team popularity does not seem to affect the relation between liquidity and market efficiency.

Table 6: Second stage results of 2SLS model estimation for BSS and $AESS$

	BSS			$AESS$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{QSPR}$	52.45** (20.54)			30.99*** (9.730)		
$\widehat{QSLP}$		846.23** (334.01)			500.01*** (159.97)	
$\widehat{LnVOL}$			-0.574** (0.242)			-0.339*** (0.119)
p^M	-2.217*** (0.186)	-2.063*** (0.213)	0.994 (1.410)	-0.958*** (0.079)	-0.867*** (0.091)	0.939 (0.680)
home	0.054 (0.038)	0.049 (0.038)	0.449** (0.182)	0.090*** (0.019)	0.086*** (0.019)	0.323*** (0.091)
away	0.029 (0.027)	0.013 (0.027)	0.384** (0.159)	0.090*** (0.015)	0.081*** (0.015)	0.230*** (0.080)
Primera División	0.051 (0.047)	0.015 (0.049)	-0.573** (0.269)	0.031 (0.021	0.010 (0.023)	-0.338** (0.132)
Season Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	2,227	2,227	2,227	2,227	2,227	2,227
$F(10; 2{,}216)$	23.85***	23.70***	19.03***	25.77***	25.16***	17.56***

Notes: The table reports the second stage estimates for the Brier skill score (BSS) and the absolute error skills score ($AESS$). The data is taken 60 minutes before the match starts. To ensure independence across observations, we randomly selected one event (*home win*, *draw*, *away win*) per match. Heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

which suggests that the negative relation between liquidity and market efficiency is robust over time.

In the following, we test whether the negative effect of liquidity on market efficiency is more pronounced on weekends when the relative fraction of uninformed noise traders is larger than on weekdays. Table 7 shows that the liquidity coefficients in the second stage regressions are considerably larger on weekends than on weekdays. Whereas liquidity significantly decreases market efficiency on weekends, the relation

Table 7: Second stage results of 2SLS model estimation for BSS for weekend and weekday matches

	BSS					
	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{QSPR}$	61.28***	18.11				
	(23.032)	(46.68)				
$\widehat{QSLP}$			966.20***	328.84		
			(366.69)	(848.24)		
$\widehat{LnVOL}$					-0.656**	-0.377
					(0.267)	(1.035)
p^M	-2.266***	-1.962***	-2.080***	-1.914***	1.396	0.282
	(0.211)	(0.392)	(0.241)	(0.453)	(1.543)	(6.303)
home	0.051	0.069	0.045	0.067	0.506**	0.336
	(0.043)	(0.079)	(0.043)	(0.078)	(0.203)	(0.759)
away	0.024	0.032	0.006	0.029	0.422**	0.320
	(0.030)	(0.070)	(0.031)	(0.065)	(0.169)	(0.832)
Primera División	0.054	0.036	0.014	0.023	-0.634**	-0.405
	(0.053)	(0.101)	(0.056)	(0.101)	(0.288)	(1.207)
Season Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1,786	441	1,786	441	1,786	441
F(10; 1,775/430)	20.45***	4.28***	20.32***	4.27***	16.50***	3.61***
F-test excl. instr.	1,637***	683***	649***	192***	30.37***	1.71

Notes: The table reports the second stage estimates for the Brier skill score (BSS) for weekend and weekday matches separately. The data is taken 60 minutes before the match starts. To ensure independence across observations, we randomly selected one event (*home win*, *draw*, *away win*) per match. The F-test of excluded instruments refers to the first stage. Heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

is not statistically significant on weekdays. Table 7 uses BSS as efficiency measure. However, the results are qualitatively the same if we use $AESS$ as efficiency measure (see Table A.2 in Appendix A.3).

5 Conclusion

This paper analyses how liquidity affects market efficiency using data from simple betting contracts with observable fundamental values traded at the betting exchange *Betfair*. To isolate the causal effect of liquidity on market efficiency we use the exogenously defined minimum spread function as an instrumental variable for liquidity. Nonparametric tests and the 2SLS results show that higher liquidity is associated with lower market efficiency. Because weekend matches are expected to exhibit more irrational noise bettors than weekday matches, we conduct a subsample analysis for weekend and weekday matches. We find that liquidity significantly decreases market efficiency for weekend matches but not for weekday matches. On weekend matches, informed bettors seem to be unable to bet aggressively enough against uninformed and sentimental noise bettors to correct mispricings.

Our findings suggest that noise trader liquidity can destabilize prices and harm market efficiency. Whereas the mispricing period in betting markets is limited by the end of the match, mispricing periods due to noise trader liquidity can last much longer in financial markets.

A Appendix

A.1 ROC and Probit Estimation

A nonparametric ROC displays the relation between hit and false alarm rates which indicates the degree of correct discrimination (I. Mason, 1982). The area under the ROC curve ranges between 0.5 and 1.0 where 0.5 reflects no discrimination skill and 1.0 perfect discrimination skill. The ROC curves for both liquidity groups are displayed in Figure A.1. The ROC curve of the *high gap MSPR* group lies mostly above the ROC curve of the *low gap MSPR* group. Therefore, the area under the ROC curve is higher for the *high gap MSPR* group (0.683) than the area for the *low gap MSPR*

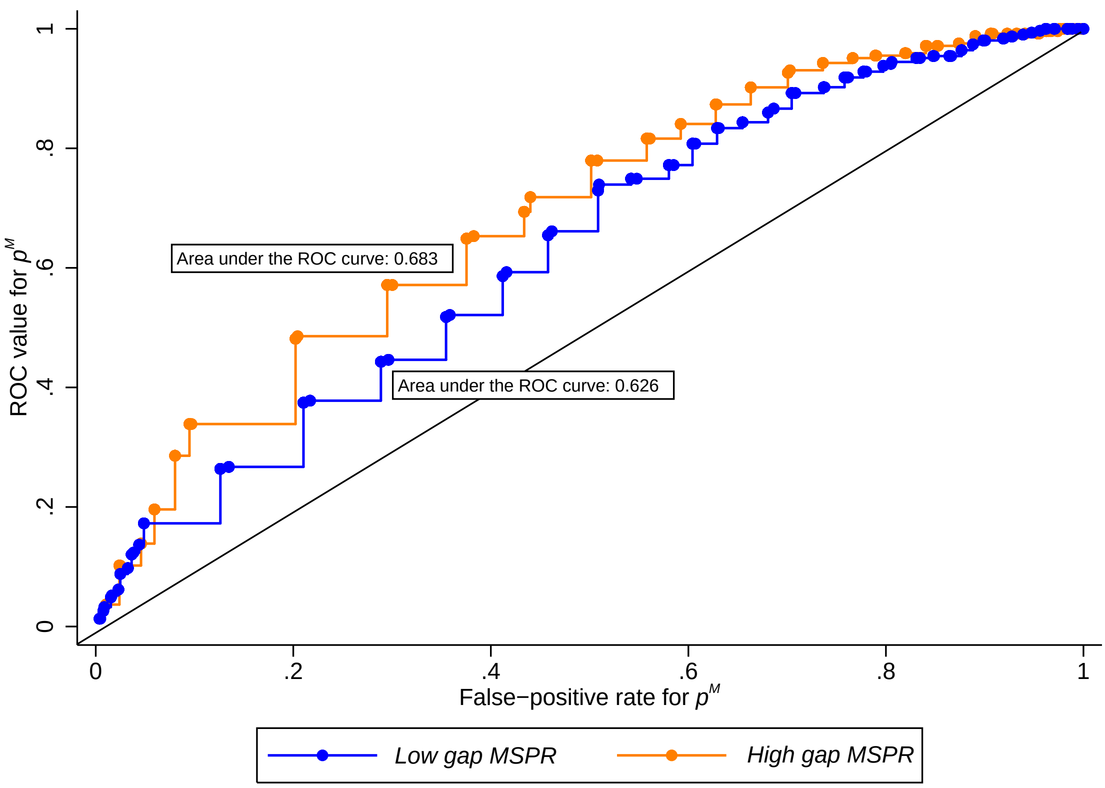


Figure A.1: Nonparametric ROC estimation group (0.626), indicating a superior discrimination ability of the forecasts from the *high gap MSPR* group.

This finding is consistent with the results from the probit regression that relates the actual outcome Y (0/1) to the midquote prices for each liquidity group displayed in Table A.1. The R^2 from the *high gap MSPR* group is 9.43% and thus higher than the R^2 from the *low gap MSPR* group of 6.10%. Therefore, the midquote prices from the *high gap MSPR* group predict the actual outcome better than the midquote prices from the *low gap MSPR* group.

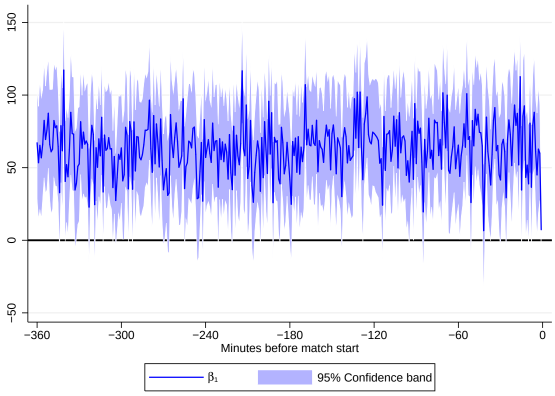
Table A.1: Results of probit estimation

	Dependent variable: outcome Y (0/1)	
	Low gap MSPR (1)	*High gap MSPR* (2)
p^M	0.841***	0.926***
	(0.100)	(0.096)
home	0.053	-0.027
	(0.035)	(0.035)
away	-0.024	-0.011
	(0.027)	(0.027)
R^2	6.10%	9.43%
N	1,353	1,204

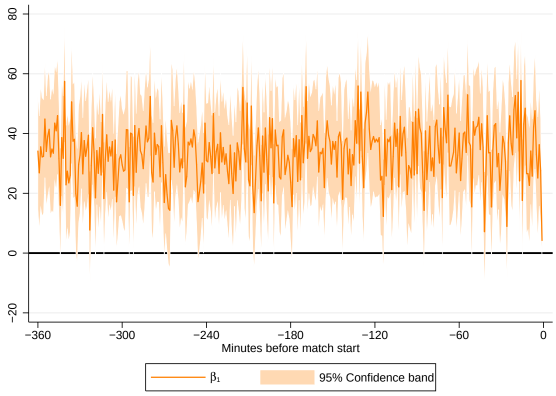
Notes: The table presents the marginal effects of a probit regression for the actual outcome of a bet (0/1) for the two groups *low gap MSPR* and *high gap MSPR*, separately. The groups are formed from observations located ± 0.025 price units around the discontinuity gaps of the $MSPR$ function. The standard errors are robust to heteroskedasticity and clustered at match level. in all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

A.2 Estimated Liquidity Effect over Time

Figure A.2 displays the coefficient estimates for the quoted spread on the Brier skill score and on the absolute error skill score over the last three hours before match start. The coefficient of $QSPR$ on BSS is always positive and seems to be stable around 50. However, there are cases in which the coefficient loses its significance. Nevertheless, over 88% of the p-values for the coefficients are smaller than 5%. For the coefficients of $QSPR$ on $AESS$, more than 92% of the p-values exhibit a value smaller than 5%. The results are qualitatively the same if we use $QSPL$ or $LnVOL$ as liquidity measures.



(a) Estimated coefficient of $QSPR$ on BSS



(b) Estimated coefficient of $QSPR$ on $AESS$

Figure A.2: Estimated coefficients over time

A.3 Estimates for *AESS* for Weekend and Weekday Matches

Table A.2: Second stage results of 2SLS estimation for $AESS$ for weekend and weekday matches

	$AESS$					
	Weekend	Weekday	Weekend	Weekday	Weekend	Weekday
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{QSPR}$	35.66***	10.96				
	(10.90)	(21.51)				
$\widehat{QSLP}$			562.18***	198.85		
			(175.78)	(392.30)		
$\widehat{LnVOL}$					-0.382***	-0.228
					(0.132)	(0.480)
p^M	-0.959***	-0.921***	-0.850***	-0.893***	1.172	0.435
	(0.090)	(0.169)	(0.104)	(0.189)	(0.750)	(2.882)
home	0.083***	0.110***	0.080***	0.109***	0.348***	0.272
	(0.022)	(0.041)	(0.022)	(0.040)	(0.102)	(0.358)
away	0.086***	0.097***	0.075***	0.095***	0.317***	0.271
	(0.017)	(0.034)	(0.017)	(0.033)	(0.085)	(0.383)
Primera División	0.036	0.008	0.013	-0.0005	-0.364**	-0.260
	(0.024)	(0.044)	(0.026)	(0.045)	(0.143)	(0.562)
Season Dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1,786	441	1,786	441	1,786	441
F(10; 1,775/430)	21.61***	5.47***	20.98***	5.43***	14.65***	4.45***
F-test excl. instr.	1,637***	683***	649***	192***	30.37***	1.71

Notes: The table reports the second stage estimates for the absolute error skill score ($AESS$) for weekend and weekday matches separately. The data is taken 60 minutes before the match starts. To ensure independence across observations, we randomly selected one event (*home win*, *draw*, *away win*) per match. The F-test of excluded instruments refers to the first stage. Heteroskedasticity-robust standard errors are reported in parentheses. In all models, *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively.

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